Reliability Based Spare Parts Management Using Genetic Algorithm

Rahul Upadhyay, Suprakash Gupta

Abstract: Effective and efficient inventory management is the key to the economic sustainability of capital intensive modern industries. Inventory grows exponentially with complexity and size of the equipment fleet. Substantial amount of capital is required for maintaining an inventory and therefore its optimization is beneficial for smooth operation of the project at minimum cost of inventory. The size and hence the cost of the inventory is influenced by a large no of factors. This makes the optimization problem complex. This work presents a model to solve the problem of optimization of spare parts inventory. The novelty of this study lies with the fact that the developed method could tackle not only the artificial test case but also a real-world industrial problem. Various investigators developed several methods and semi-analytical tools for obtaining optimum solutions for this problem. In this study, non-traditional optimization tool namely genetic algorithms (GA) are utilized. Apart from this, Cox's regression analysis is also used to incorporate the effect of some environmental factors on the demand of spares. It shows the efficacy of the applicability of non-traditional optimization tool like GA to solve these problems. This research illustrates the proposed model with the analysis of data taken from a fleet of dumper operated in a large surface coal mine. The optimum time schedules so suggested by this GA-based model are found to be cost effective. A sensitivity analysis is also conducted for this industrial problem. Objective function is developed and the factors like the effect of season and production pressure overloading towards financial year-ending is included in the equations. Statistical analysis of the collected operational and performance data were carried out with the help of Easy-Fit Ver-5.5.The analysis gives the shape and scale parameter of theoretical Weibull distribution. The Cox's regression coefficient corresponding to excessive loading and rainfall was obtained in IBM-SPSS Ver-23. The objective function so developed is programmed in MATLAB-2013 and run in Genetic Algorithm environment to obtain the minimum total cost of the inventory. And finally the sensitivity analysis is carried out for this industrial case study problem to find out which component of the cost has greater impact on the total cost of inventory.

Key words: Spare parts, Management, Genetic Algorithm.

1. Introduction

With more and more technological advances made available nowadays, the manufacturing industry is producing various types of equipment worth billions of dollars for use by the mining industry throughout the world (Peng and Vayenas 2013[11]). For instance, as per the United States Census Bureau in 2008, American mining equipment manufacturers shipped approximately $4.0 billion worth of goods , compared to $2 billion in 2005 .Within these 2008 figures, underground mining machinery (except parts sold separately) accounted for $1.0billion,or 25percent. It is worthwhile to mention that portable drilling rigs and parts accounted for $1.7 billion or 42.5 percent. In some mines, maintenance cost might take up to 50 to 60 percent of total costs. Today, the global economic recession is forcing mining companies to modernize their operations through increased mechanization and automation (US Census Bureau 2009[12]). To this end, it is desirable to design and utilize mining equipment systems with better reliability and maintainability both for engineers and mining managers should function in acceptable level of reliability. Otherwise, important losses can be occurred from standpoints of safety, quality, health, environment and finance (Peng and Vayenas 2013[11]). Based on an analysis in 2012 conducted by the International Air Transport Association (IATA)'s Maintenance Cost Task Force (MCTF, 2012[4]), the maintenance cost takes up about 13% of the total operating cost, and it can be reduced by a good planning. On the other hand, an excellent maintenance program can effectively avoid breakdown, thus improve customer satisfaction and competitiveness in the industry. Spare parts inventories exist to serve the maintenance planning. An excess of spare parts inventory leads to a high holding cost and impedes cash flows, whereas inadequate spare parts can result in costly operations or delays with a negative impact on industry performance. Since the mining industry involves with a large number of parts and some of them are quite expensive, it is important to find an appropriate inventory model to achieve a right balance (Jingyao Gu and Guoqing Zhang et al 2013[5]). Global competitions, shorter life cycles, dynamic changes of demand pattern and product varieties and environment standards cause significant changes in the market thereby thrusting immense pressure on the manufacturing enterprises in order to strive in such a dynamic place (Sarmiento et al 2007[1]). Reduction of lead times and expenses, enhancement of customer service levels and improvement of product quality are some of the key features that determine the competitiveness of a company in the contemporary market place (Joines and Thoney 2008[2]). These factors have made the business organizations contemplate on their supply chain. Spare parts prediction and optimization is a complex problem and requires the identification of all influence factors as well as the selection of an appropriate model for quantifying their effect on the required number of spare parts. Some of the important influence factors are the operational conditions, including climatic conditions (temperature, wind, snow, dust, ice, etc.), the skill of the operator and maintenance crew, the history of the repair activities carried out on the machine, etc. Ghodrati and Kumar showed that in the Kiruna Mine, Sweden, ignoring the effects of operational conditions can lead to a 20% difference in the expected numbers of required spare parts for the hydraulic jacks in a Load-Haul-Dump machine in one year (Barabadi and Markeset 2013[15]). Hence efficient and effective management of inventory is the need for the hour owing to the constant increase in the customer service levels. The total supply chain may be affected by having excess inventories and shortage of inventories. Inventory is held throughout the supply chain in the form of raw materials, work in progress, and finished goods (Barnabas and Edwards 2013[14]). Consequently, inventory optimization is one of the hottest topics when the supply chain management is considered (P. Radhakrishnan and V.M Prasad 2009[3]). In this paper, a new model is proposed in which the objective is to minimize the total cost rate of spare parts inventory. The effect of various environmental conditions like rainfall and excessive loading on machine is incorporated to predict the estimation of spare parts. Various parameters are involved in the optimization process and therefore, traditional optimizations might need some algorithms that require long calculation times/semi-numerical procedures. In this study, Genetic Algorithms (GA) has been utilized for the optimization problem. Industrial data for a dumper are gathered from a mining industry and the developed model is applied for optimization of total cost rate.

2. Literature review

Spare parts inventories are different from other types of inventories in companies. Cohen and Lee (1990), Cohen, Zheng and Agrawal (1997), Muckstadt (2004), Kumar (2005) and Rego (2006) have pointed out some important factors in the management of these inventories:

- Customers have rising expectations concerning quality of associated products and services. The occurrence of failure is already a concern and the delay in repairing due to lack of spare parts worsens clients' negative perception;
- Some items have high demand (parts with great wearing and those related to preventive maintenance), but the great majority has intermittent demand and;
- The increasing complexity of products and the life cycles reduction generate an increase on the amount of active codes and risk of obsolescence. Initially, it is important to distinguish disposable parts from repairable ones. Spare parts are extremely expensive in some segments, and their repair (instead of discard) is feasible; damaged units can be replaced either by new units or by repaired ones. In this case, the inventory control models should also consider the costs and repair time (Jose Roberto do Rego 2011[6]).

Maintenance techniques have changed over time from correction (breakdown) to prevention by prediction and proactive continuous improvement. Their main goal is to ensure that the system performs its function as intended. In order to achieve that, the efficient spare parts management is required. The lack of spare parts when they are needed leads to unexpected downtimes and irreparable loss for a company. The aircraft are modern high-tech means of transport. They consist of a large number of components and parts. Each component is exposed to varying degrees of stress, with its own maintenance plan. Downtimes and costs can be reduced if a failure occurrence is forecasted and maintenance planned accordingly. If a spare part needed for replacement is unavailable, additional costs will occur. Some consequences such as damage to a mining company's reputation due to downtimes are difficult to quantify. This is why the problem of spare parts forecasting in aviation still persists. The main problem is to retain a required level of aircraft availability, that is, to provide the appropriate spare part at the right time and in the right place. The interest in inventory management has been increased in recent times but majority of maintenance service companies felt that spare parts forecasting methods are not providing them with realistic results in practice so they tried to outguess the forecast. Uncertainty of events, failure of equipment, and components has significant effect on their maintenance. These failures are random processes. It is not always possible to predict their occurrence. In order to minimize the equipment downtime and increase availability, one approach is to maintain the appropriate level of spare parts. If we keep more spare parts than required, unnecessary warehousing costs will occur. In the opposite case, if their level is less than required, certain delay costs will occur. Therefore, the goal is to maintain the level of spare parts which provides minimum warehousing and delay costs on one side, while guaranteeing a high level of availability of spare parts on the other (Nataša Z. Kontrec. and Gradimir V. MilovanoviT 2015[7]). Classical inventory model developed by Harris (1913)[22] provided a simple formulation for the economic order quantity (EOQ) that could minimize the total inventory cost. This model was extensively applied by Wilson (1934)[23]. It was further developed to suit real-life situations by various investigators. Jaber (2009)[24] presented some of the non-classical approaches to inventory management. Mathematical theory of reliability was developed by Barlow and Proschan (1965)[25]. Fundamental and theoretical work in the areas of reliability was detailed by Pham (2003)[26]. Nakagawa (2005)[27] discussed some maintenance policies that could be applicable to modern industrial environment. Reliability and optimal maintenance had been discussed by Wang and Pham (2006)[28]. Early attempts to apply classical inventory analysis to spare parts inventory could be seen in the work by Flowers and O'Neill (1978)[29]. Studies on optimization in the above field were started around the same time (Kaio and Osaki 1978[30]; Yamada and Osaki 1981[31]). In 1986, Acharya et al. (1986)[32] developed a policy for joint optimization of block-replacement and spares. They found that the jointly optimal preventive replacement interval is appreciably different from the corresponding optimal preventive replacement interval, where only the replacement related costs were considered. Ghodrati and Kumar (2005)[16] developed the methods for forecasting requirement of maintenance spares. Generalized spare ordering policies were investigated by Chien (2005)[33]. Ilgin and Tunali (2007)[34] utilized a GA for joint optimization of spare parts and maintenance policies. Gharbi et al. (2007)[35] developed a model that could determine optimal safety stocks and preventive maintenance periods. Rausch and Liao (2010)[36] modeled production and spare part inventory control for condition-based maintenance. The failure process was modeled as a non-homogeneous Poisson process in the optimal spare ordering model by Chen and Chien (2010)[37]. A comprehensive review of spare parts management was carried out by Boylan and Syntetos (2010)[21] in the same year. Xu et al (2011)[38] utilized numerical methods (in Matlab) to obtain solution to the problem of joint optimization of spare stock and age-based replacement policy. Basten et al. (2012)[39] modeled the joint problem of level of repair cum spare parts stocking and found out that lower overall costs could be achieved by combining the two objectives. Kurnaiti et al. (2013)[40] found out that failure data collected from the field could be useful in the development of optimum policies. In recent times, Chen et al. (2013)[41] developed an analytical framework, which could minimize the undiscounted long-run average cost under availability constraint for joint maintenance and spare parts provisioning. Xiao and Peng (2014)[42] utilized a

GA to evaluate the system's availability of multi-state elements in series-parallel systems. The effects of external factors like environment, maintenance policy, skill of operator etc. on the reliability and consequently, the requirement of spare parts was investigated by Barabadi et al. (2014)[15].

3. Genetic algorithm as a tool and technique

In the 1950s and the 1960s several computer scientists independently studied evolutionary systems with the idea that evolution could be used as an optimization tool for engineering problems. The idea in all these systems was to evolve a population of candidate solutions to a given problem, using operators inspired by natural genetic variation and natural selection. Genetic algorithms (GAs) were invented by John Holland in the 1960s and were developed by Holland and his student David Goldberg and colleagues at the University of Michigan in the 1960s and the 1970s. The working principle of GA consists of the following steps:

1. Generation of a set of initial solutions at random.
2. Evaluation of fitness of each individual solution.
3. Selection of suitable solutions for the next generation using reproduction scheme.
4. Breeding of new candidate solutions through crossover and mutation.
5. Evaluation of fitness of new solutions so generated.
6. Repetition of steps 3–5 above, till designated termination criterion is reached

Genetic algorithms (GAs) are search techniques based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a randomized information exchange to form a search algorithm with some of the innovative flair of human search. In every generation, a new set of artificial creatures is created using bits and pieces of the fittest of the old; an occasional new part is tried for good measure. They efficiently exploit information to speculate on new search points with an expected improved performance. (Goldberg, David E.[5]).GA is different from traditional optimization and search procedure in the following ways:

1. GAs work with a coding of parameter set, not the parameter themselves.
2. GAs search from a population of points, not a single point.
3. GAs use objective function information, not derivatives or other auxiliary knowledge.
4. GAs use probabilistic transition rule, not deterministic rules.

A simple Genetic Algorithm that yields good results in many practical problems is composed of three operations:

1. Selection
2. Crossover
3. Mutation

4 Methodology of working

The ability to predict the occurrence of failure is central to development of preventive maintenance models. A reasonable and fairly accurate evaluation of the number of likely failures in a given time interval has been carried out, the next activity would be to evaluate the requirement of maintenance spares. Thereafter, the costs towards maintenance and spares parts could be combined in a suitable way and further analysis might be carried out for optimization of the total cost. Further, it has also been observed that failure of a working machine may follow various types of probability distribution functions. Moreover, the performance of an optimization tool is found to be problem-dependent. Therefore, it is felt that the better results might be obtained, if non-traditional optimization tools like GA algorithm were utilized instead, which could provide optimal solutions irrespective of the complexity of the objective functions. Developed model for spare parts inventory management is a step by step as detailed below.

1. Identification of various cost components of spare parts inventory for optimization
2. Development of objective cost function.
3. Collection of field Data.
4. Analysis of collected field data using Easy-Fit Ver-5.5.
5. Use of SPSS and MATLAB for modelling and optimization.

4.1 Different annexed costs of inventory

Different types of cost associated with inventory are:-

1. Cost of item**:** This accounts the MRP of spare parts.
2. Cost of ordering**:** It is the cost which is incurred when we place an order for a particular spare part. Cost of ordering includes various costs such as
   - 2.1 Cost of transportation
   - 2.2 Cost of people working in purchasing
   - 2.3 Delay cost etc.
3. Cost of Holding or Carrying Cost**:** When we purchase a particular spare part then it has to be stored in the inventory. Some amount of cost is incurred while placing an item in the inventory. Cost of Holding includes
   - 3.1 cost of storage
   - 3.2 cost of power
   - 3.3 cost of inspection etc.
4. Cost of backordering (when there is shortage**):** Backordering costs are associated with not being able to fill an order. For example, company xyz sells widgets. On black Friday, it offers 30% off all widgets online, and it receives an unprecedented number of orders: 500,000 units in four hours. It has only 400,000 units in the warehouse and will need three weeks to make the missing 100,000 units. These units are backordered.

4.2 Development of objective function

Our objective is to minimize the total cost of spare parts.

Minimize TC=COI+CO+COH+COB

COI- cost of item.
CO- cost of ordering.
COH- cost of holding.
COB- cost of backordering.

$$\text{Minimize} \qquad \mathrm{TC} = \frac{\mathrm{C_I} + \mathrm{C_O} + \mathrm{C_H} + \mathrm{C_{BO}}}{\mathrm{T} + \Delta\mathrm{T}}$$

TC- total cost rate.
C_I= cost of items.

C_o= cost of ordering the item.
C_H= cost of holding or carrying the item in the inventory.
C_{BO}= Total value of backordering cost.

In the above equation, each cost component requires number of spare parts and number of spare parts needed depends on number of failure in that planning period. We want to include the effect of environmental conditions on number of failures. Hence Cox's proportion hazard model could be the best to include the effect of these environmental conditions on hazard rate.

4.2.1 Introduction of Cox's Model

The Cox model expresses the relationship between the hazard and a set of variables or covariates.These could be arm of trial, age, gender, social deprivation, Dukes stage, co-morbidity, etc. by D.R. Cox. Cox introduced the concept of "maximum partial likelihood" in 1972[44], through his most frequently cited articles in statistics and medicine, Regression models and life tables. Cox models the effect of covariates on hazard rate but leave the baseline hazard rate unspecified. It does not assume knowledge of absolute risk but rather estimate relative than absolute risk.

$$h(t) = \lim_{\Delta t \longrightarrow 0} \frac{P(t \le T < t + \Delta t / T \ge t)}{\Delta t}$$

In words: the probability that **if you survive to t**, you will succumb to the event in the next instant.

$$\text{Hazard from density and survival: } h(t) = \frac{f(t)}{S(t)}$$

Components:

- A baseline hazard function that is left unspecified but must be positive (=the hazard when all covariates are 0)
- A linear function of a set of k fixed covariates that are exponentiated. (=the relative risk)

$$h_i(t) = \lambda_0(t) e^{\beta_1 x_{i1} + \ldots + \beta_k x_{ik}}$$

Taking log both side

$$\log h_i(t) = \log \lambda_0(t) + \beta_1 x_{i1} + \ldots + \beta_k x_{ik}$$

4.2.2 Objective function using Cox Model

$$\text{Minimize} \qquad TC = \frac{C_I + C_O + C_H + C_{BO}}{T + \Delta T}$$

$$h(t,z) = h_o(t) * \emptyset(\beta z)$$

$$h_o(t) = \frac{\alpha}{\beta} * \left(\frac{t}{\alpha}\right)^{\beta-1}$$

$$h(t,z) = h_o(t) * e^{\beta_1 z_1 + \beta_2 z_2}$$

$h_o(t)$=Baseline hazard function.
$h(t,z)$= hazard function including covariate.
β= coefficients of covariates.
Z= covariates.

If n_f represents the number of failures in a given interval then it can be given as:

$$n_f = \int_0^T h(t,z)\, dt$$

T= time interval for planning.

$$C_I = C_i * \int_0^T h(t,z)\, dt$$

$$C_I = C_i * \int_0^T h_o(t) * e^{\beta_1 z_1 + \beta_2 z_2}\, dt$$

$$C_I = C_i * \int_0^T \frac{\alpha}{\beta} * \left(\frac{t}{\alpha}\right)^{\beta-1} * e^{\beta_1 z_1 + \beta_2 z_2}\, dt$$

C_I= Total cost of items.
C_i=cost per unit item per unit time.
C_o=cost of ordering.

$$C_H = C_h * \int_0^T [H(T) - h(t,z)]\, dt$$

Variation of stock maintenance spare parts kits with time is shown in the figure-10 below.

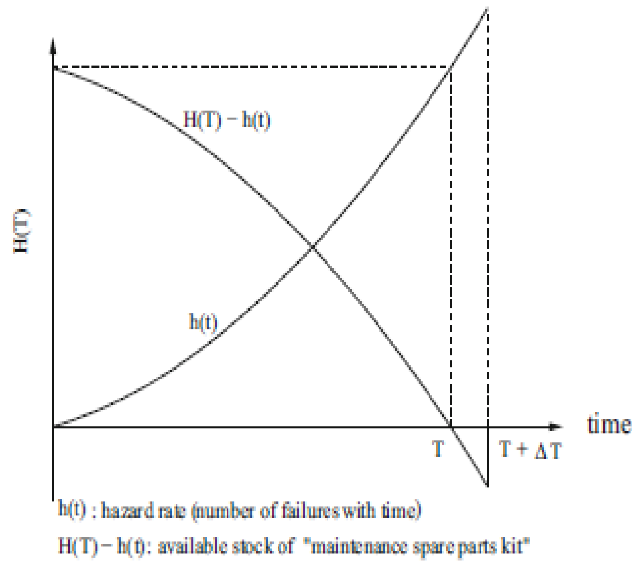

***Fig: - 10.** Variation of stock maintenance spare parts kits with time (Samal and Pratihar 2015[13])*

$$H(T) = \int_0^T h(t,z) dt$$

$$C_H = C_h * \int_0^T \left| \int_0^T h(t,z) dt - h_o(t) * e^{\beta_1 z_1 + \beta_2 z_2} \right| dt$$

$$C_H = C_h * \int_0^T \left| \int_0^T h(t,z) dt - \frac{\alpha}{\beta} * \left(\frac{t}{\alpha}\right)^{\beta-1} * e^{\beta_1 z_1 + \beta_2 z_2} \right| dt$$

H(T)=cumulative hazard function.
C_H=total cost of holding or carrying cost.
C_h=holding cost per unit item.

$$C_{BO} = C_{bo} * \int_{T}^{T+\Delta T} h(t,z)dt$$

$$C_{BO} = C_{bo} * \int_{T}^{T+\Delta T} h_o(t) * e^{\beta_1 z_1 + \beta_2 z_2} dt$$

$$C_{BO} = C_{bo} * \int_{T}^{T+\Delta T} h_o(t) * e^{\beta_1 z_1 + \beta_2 z_2} dt$$

$$C_{BO} = C_{bo} * \int_{T}^{T+\Delta T} \frac{\alpha}{\beta} * \left(\frac{t}{\alpha}\right)^{\beta-1} * e^{\beta_1 z_1 + \beta_2 z_2} dt$$

C_{BO}=Total value of backordering cost.
C_{bo}= backordering cost per unit time in Rs.

Therefore combining all the above cost our objective function formulates as follows:

$$TC = \frac{C_i * \int_0^T \frac{\alpha}{\beta} * \left(\frac{t}{\alpha}\right)^{\beta-1} * e^{\beta_1 z_1 + \beta_2 z_2} dt + C_o + C_h * \int_0^T \left[\int_0^T h(t,z)dt - \frac{\alpha}{\beta} * \left(\frac{t}{\alpha}\right)^{\beta-1} * e^{\beta_1 z_1 + \beta_2 z_2}\right] dt + C_{bo} * \int_T^{T+\Delta T} \frac{\alpha}{\beta} * \left(\frac{t}{\alpha}\right)^{\beta-1} * e^{\beta_1 z_1 + \beta_2 z_2} dt}{T + \Delta T}$$

4.3 Real data from industry
To develop the proposed model, equipment performance and operational data were collected from a large surface coal situated in northern India.

4.3.1 Breakdown data of Dumpers
The failure data of dumpers for the year 2015-16 is given below.

MODEL:-777D100

S.NO	MONTH	CAUES OF FAILURE	DOWNTIME	UPTIME	FREQUENCY OF FAILURE	TTF
1	Apr-15	valve failure	202.61	517.58	41	12.62
2	May-15	"	314.28	429.71	48	8.15
3	Jun-15	"	386.71	333.28	30	11.1
4	Jul-15	"	345.4	348.6	19	18.34
5	Aug-15	"	453.96	290.03	38	7.6
6	Sep-15	"	92.21	627.78	21	29.89
7	Oct-15	"	168.51	575.48	39	14.75
8	Nov-15	"	131.31	588.68	25	23.54
9	Dec-15	"	288.16	455.83	39	11.63
10	Jan-16	"	291.51	452.48	50	9.04
11	Feb-16	"	299.56	372.44	51	7.31

MODEL:-777D100

S.NO	MONTH	DESCRIPTION	DOWNTIME	UPTIME	FREQUENCY OF FAILURE	TTF
1	Apr-15	Checklight	232.8	487.2	48	10.15
2	May-15	"	191.4	552.6	52	10.62
3	Jun-15	"	270.11	449.89	36	12.49
4	Jul-15	"	395.4	348.6	18	19.36
5	Aug-15	"	145.45	598.55	42	14.25
6	Sep-15	"	645.01	74.99	44	1.7
7	Oct-15	"	81.05	662.95	26	25.49
8	Nov-15	"	252.7	467.3	66	7.08
9	Dec-15	"	154.11	589.89	41	14.38
10	Jan-16	"	165.18	578.82	34	17.02
11	Feb-16	"	145.48	550.52	42	13.107

MODEL:-777D100

S.NO.	MONTH	CAUSE OF FAILURE	DOWNTIME	UPTIME	FREQUENCY OF FAILURE	TTF
1	Apr-15	Oil-filter	43.86	676.14	13	52.01077
2	May-15	"	242.88	501.12	21	23.86286
3	Jun-15	"	359.9	360.1	19	18.95263
4	Jul-15	"	117.63	626.37	12	52.1975
5	Aug-15	"	168.53	575.47	28	20.5525
6	Sep-15	"	545.86	174.14	24	7.255833
7	Oct-15	"	484.31	259.69	16	16.23063
8	Nov-15	"	114.03	605.97	12	50.4975
9	Dec-15	"	393.78	350.22	16	21.88875
10	Jan-16	"	564.71	179.29	26	6.895769
11	Feb-16	"	545.68	150.32	28	5.368571

4.3.2 Production Data
Below is the production data for year 2014 to 2015.

PRODUCTION DATA -2015

S.NO.	MONTH	OBR(Te)	COAL(Te)
1	Apr-15	286005	227000
2	May-15	207000	290000
3	Jun-15	215004	324000
4	Jul-15	129000	374000
5	Aug-15	257000	358000
6	Sep-15	200000	373000
7	Oct-15	224000	334000
8	Nov-15	209000	411000
9	Dec-15	220000	443000

PRODUCTION DATA -(2014-15)

S.NO.	MONTH	OBR	COAL
1	Apr-14	537000	223000
2	May-14	492000	290000
3	Jun-14	446000	307000
4	Jul-14	462000	283000
5	Aug-14	299000	256000
6	Sep-14	317000	175000
7	Oct-14	301000	265000
8	Nov-14	281000	300000
9	Dec-14	167000	401000
10	Jan-15	21000	317000
11	Feb-15	152000	358000
12	Mar-15	50000	522000

4.3.3 Inventory Cost Analysis Data

The inventory cost data for year 2015-16 is given below.

INVENTORY COST

S.NO	MONTH	Rsin crores
1	Apr-15	13.71
2	May-15	14.59
3	Jun-15	15.43
4	Jul-15	15.66
5	Aug-15	16.01
6	Sep-15	16.48
7	Oct-15	16.36
8	Nov-15	15.25
9	Dec-15	14.29
10	Jan-16	13.25
11	Feb-16	14.25

MONTH Rs. In crores

Total/Dumper=Rs 6,85,500.665
Total/Spare=6,85,500.665/30
=22,580

Cost of holding=Rs 18829.66

Cost of ordering=Rs 29939.20

cost of back-ordering=Rs 26549.70

5. Result and Discussions

5.1 Results

Analysing the breakdown data of dumpers that were collected from the field, it was observed that failures in a dumper are occurring due to failure of various parts. But major causes of failures are valve failure, oil filter leakage and check-light failure. Also from the inventory analysis it was estimated that the cost of items (spare parts) such as control valve, oil-filter and check-light are Rs 3480, Rs 2924, and Rs 5984. In the absence of exact cost data for the different components of cost such as cost of ordering, cost of holding or carrying cost and cost of backordering are assessed from the collected information and estimated as Rs 29,939.20, Rs 26,549.70 and Rs 18829.66 respectively. The objective function of cost rate due to control valve failure is as follows.

$$TC = \frac{3480 * \int_0^T 0.0167(t)^{1.5}\ dt + 29939.2 + 18829.6 * \int_0^T \left[\int_0^T 0.0167(t)^{1.5} dt - 0.0167(t)^{1.5}\right] dt + 26549.7 * \int_T^{T+\Delta T} 0.0167(t)^{1.5} dt}{T + \Delta T}$$

Similarly objective function of cost rate due to oil filter failure and check-light failure are as follows.

$$TC = \frac{2924 * \int_0^T 0.1165(t)^{0.23}\ dt + 29939.2 + 18829.6 * \int_0^T \left[\int_0^T 0.1165(t)^{0.23} dt - 0.1165(t)^{0.23}\right] dt + 26549.7 * \int_T^{T+\Delta T} 0.1165(t)^{0.23} dt}{T + \Delta T}$$

$$TC = \frac{5984 * \int_0^T 0.1975(t)^{0.29}\ dt + 29939.2 + 18829.6 * \int_0^T \left[\int_0^T 0.1975(t)^{0.29} dt - 0.1975(t)^{0.29}\right] dt + 26549.7 * \int_T^{T+\Delta T} 0.1975(t)^{0.29} dt}{T + \Delta T}$$

Therefore our optimization equations are as follows.

1. Minimize:

$$TC = \frac{3480 * \int_0^T 0.0167(t)^{1.5}\ dt + 29939.2 + 18829.6 * \int_0^T \left[\int_0^T 0.0167(t)^{1.5} dt - 0.0167(t)^{1.5}\right] dt + 26549.7 * \int_T^{T+\Delta T} 0.0167(t)^{1.5} dt}{T + \Delta T}$$

Subject to:

T∈ [0 1.5]
ΔT∈ [0 0.1]

2. Minimize:

$$TC = \frac{2924 * \int_0^T 0.1165(t)^{0.23}\ dt + 29939.2 + 18829.6 * \int_0^T \left[\int_0^T 0.1165(t)^{0.23} dt - 0.1165(t)^{0.23}\right] dt + 26549.7 * \int_T^{T+\Delta T} 0.1165(t)^{0.23} dt}{T + \Delta T}$$

Subject to:
T∈ [0 1.5]
ΔT∈ [0 0.1]

3. Minimize:

$$TC = \frac{5984 * \int_0^T 0.1975(t)^{0.29}\ dt + 29939.2 + 18829.6 * \int_0^T \left[\int_0^T 0.1975(t)^{0.29} dt - 0.1975(t)^{0.29}\right] dt + 26549.7 * \int_T^{T+\Delta T} 0.1975(t)^{0.29} dt}{T + \Delta T}$$

Subject to:
T∈ [0 1.5]
ΔT∈ [0 0.1]

Genetic algorithms work with a coding of variables and need design space to be converted into genetic space. As GA uses a set of points at a time from a population in contrast to the single point approach by traditional optimization methods, therefore, it generates a population of points at the end of the iteration. The best set of point in the population reaches the optimal solution. At each step, GA selects individuals at random from the current population to be parents and uses them to reproduce the children for the next generation. Over successive generations, the population evolves toward an optimal solution. The genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

1. Selection rules select the individuals, called parents that contribute to the population in the next generation.
2. Crossover rules combine two parents to form children for the next generation.
3. Mutation rules apply random changes to individual parents to form children

As discussed above GAs deal with the population of points rather than a single point called as population size. Larger the population size better would be the accuracy of results. So in this case the population size-20 was used for reasonable accuracy. There are a number of selection strategies such as Roulette-wheel selection, Tournament selection, Rank selection, stochastic uniform selection, etc. In this model, selection rule used is Roulette wheel selection. Roulette simulates a roulette wheel with the area of each segment proportional to its expectation. The algorithm then uses a random number to select one of the sections with a probability equal to its area. Crossover combines two individuals, or parents, to form a new individual, or child, for the next generation. After the completion of the selection phase, then the crossover operator comes into play its role. Crossover operator is a recombination operator and selects a pair of two individual strings for mating, then a cross-site is selected at random along the string length and the position values are swapped between two strings following the cross-site. There exist many types of crossover operations in genetic algorithms such as single-site crossover, Two-point crossover, multipoint crossover etc. In this work scattered crossover is used for obtaining results. Scattering creates a random binary vector. It then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child. For example:

p1 = [a b c d e f g h]
p2 = [1 2 3 4 5 6 7 8]
Random crossover vector = [1 1 0 0 1 0 0 0]
Child = [a b 3 4 e 6 7 8]

In GA the term crossover rate is usually defined as the ratio of the number of pairs to be crossed to some fixed population. Typically varies from 0.5 to 1 and here it is assumed as 0.8. After cross over, the strings are subjected to mutation. Mutation of a bit involves flipping it, changing 0 to 1 and vice versa with a very small mutation probability. The mutation rate is the probability of mutation which is used to calculate the number of bits to be muted. The probability varies from0.001 to 0.5. Using the MATLAB-2013a, running the code in the optimization toolbox of MATLAB, the results obtained are as follows: In case of valve failure running the code in MATLAB, on 54 iterations the total cost comes about 18913.8 and the value of T and ΔT are 1.5 and 0.1. Figure 10 shows the best function value of each generation with the number of iterations. Here the program terminates after 54 iterations and the fitness value at the end of the iteration is shown in the figure 12 that clearly shows that the fitness value decreases after first iteration and after that it keeps on decreasing continuously and the program terminates after iteration 54.

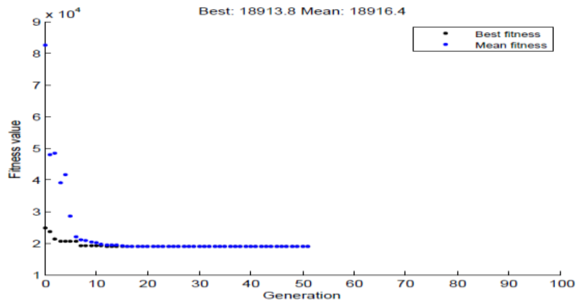

***Fig: - 12** Change of best fitness value with generation for valve*

Similarly for oil leakage filter failure, the total cost comes around Rs 20128.60 and the value of T and ΔT are 1.5 and 0.1 respectively on 51 iterations as shown in figure 13.

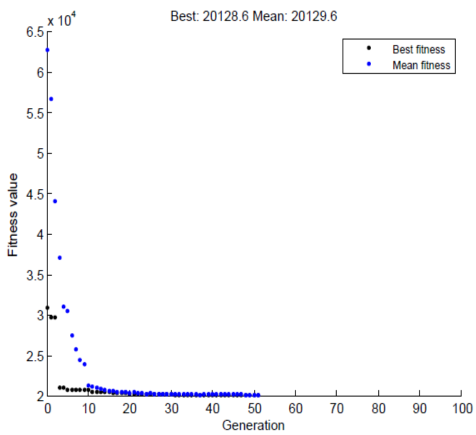

***Fig: - 13** Change of best fitness value with generation for oil filter*

And finally for check-light failure, the total cost comes around Rs21570.50 and the value of T and ΔT are 1.5 and 0.1 respectively on 51 iterations as shown in figure 14.

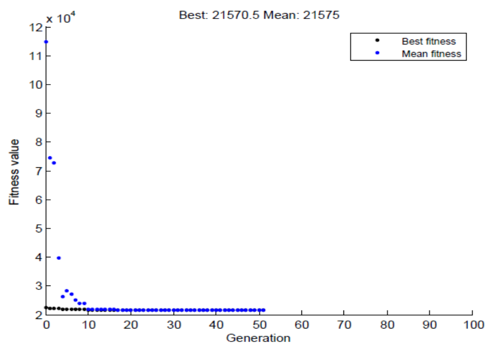

***Fig: - 14** Change of best fitness value with generation for check light*

So the above results clearly shows that using the Genetic Algorithm the Inventory monthly cost of spare parts comes less than what we had obtained from the mining field.

5.2 Calculation of number of spare parts needed:

The approximate number of spare parts N_t during the planning horizon t is given by:

$$N_t = \frac{t}{T} + \frac{\varsigma^2 - 1}{2} + \varsigma\sqrt{\frac{t}{T}}\Phi^{-1}(p)$$

T = TTF -time to failure
ς = coefficient of variation of TTF=σ (T)/T
$\Phi^{-1}(p)$= inverse normal distribution function
σ (T)= standard deviation of TTF.

$$h(t,z) = h_o(t) * \emptyset(\beta z)$$
$$h_o(t) = \frac{\alpha_0}{\beta_0} * \left(\frac{t}{\alpha_0}\right)^{\beta_0 - 1}$$
$$h(t,z) = h_o(t) * e^{\beta_1 z_1 + \beta_2 z_2}$$

This equation indicates the Weibull distribution, with shape parameter and scale parameter as:

$$\alpha = \alpha_0$$
$$\beta = \beta_0 * \left(e^{\beta_1 z_1 + \beta_2 z_2}\right)^{\frac{-1}{\beta_0}}$$

Whereα_0 and β_0 are the initial (baseline) shape and scale parameters respectively in the Weibull distribution. The coefficient of variation of the TTF can be calculated based on the shape and scale parameter as follows.

ς=σ (T)/T

Where
T=βΓ́ $(1 + \frac{1}{\alpha})$
σ (T)=β$\sqrt{Γ́\left(1 + \frac{2}{\alpha}\right) - Γ́^2\left(1 + \frac{1}{\alpha}\right)}$
K=$e^{\beta_1 z_1 + \beta_2 z_2}$ = 5.0632
β_0=14.20
α_0= 2.5
T=6.4777
σ (T)=1.0692
ς=0.1651

$$N_t = \frac{560}{6.477} + \frac{0.1651^2 - 1}{2} + 0.1651\sqrt{\frac{560}{6.477}}\ 1.645$$

N_t=88.49≈89 spare parts

5.3 Sensitivity analysis:

In order to find out the variable(s), that could have the maximum impact on the fitness function, a sensitivity analysis was carried out. In this the three costs parts of TC are varied within ±2% on both sides (lower and higher) of their initial values as shown in Table 4, Table 5 and Table 6. The observation of sensitivity analysis is that Inventory ordering cost has the highest impact on the total cost rate. Variation in the backordering cost and holding cost hardly has any impact on the value of total cost rate (TC).

Table 4 *Sensitivity analysis: inventory- Variation in C_0 keeping C_h and C_{bo} constant (Rs)*

Variation in C_0 keeping C_h and C_{bo} constant (Rs)	TC (Rs)	T (months)	ΔT (months)
28740	18164.16	1.5	0.1
29340	18539.13	1.5	0.1
29940	18914.13	1.5	0.1
30540	19289.13	1.5	0.1
31140	19664.18	1.5	0.1

Table 5 *Sensitivity analysis: inventory- Variation in C_h keeping C_o and C_{bo} constant (Rs)*

Variation in C_h keeping C_o and C_{bo} constant (Rs)	TC (Rs)	T (months)	ΔT (months)
18076	18909.50	1.5	0.1
18453	18911.83	1.5	0.1
18830	18914.13	1.5	0.1
19207	18916.00	1.5	0.1
19584	18918.21	1.5	0.1

Table 6 *Sensitivity analysis: inventory- Variation in C_{bo} keeping C_h and C_o constant (Rs)*

Variation in C_{bo} keeping C_h and C_o constant (Rs)	TC (Rs)	T (months)	ΔT (months)
25484	18911.74	1.5	0.1
26017	18912.89	1.5	0.1
26550	18913.83	1.5	0.1
27083	18914.93	1.5	0.1
27616	18915.98	1.5	0.1

6. Conclusion

Efficient and effective management of inventory is the need of the hour owing to the constant increase in the customer service levels. It is observed that machine failure does not occur only due to wear out of machine but the environmental factors such as overloading of machine primarily during excessive production pressure period, human skills, and environmental conditions etc. affect the failure rate of machine. Therefore determining the hazard rate considering the environmental factors would be more appropriate. Proper attention to these environmental factors can enhance the availability of spare parts and hence machines, resulting in economical operation. This work concludes that real life objectives are very stochastic in nature and also include various parameters. Various parameters are involved in the objective of the problem therefore traditional optimization methods might need some algorithms that require long calculation times/semi-numerical procedures. The beauty of using Genetic Algorithm is that it escapes the route of complex mathematical calculation and does not stuck in local minima or maxima. On account of the inherent mathematical complexity of objective function, it is felt that tools like GA might be useful for obtaining the optimal values, rather than heuristic or semi-analytical methods. Real life breakdown data of dumper was obtained from the field study. The work suggested an alternative time schedule, which turned out to be more economical, in comparison to the current practice being followed by the industry. It is seen that present time interval of one year is not the optimal one. The total cost rate for a spare as of now is Rs 22850 per month. On the other hand GA could suggest the optimal value of T as 1.5 months and the value of total cost rate turned out to be equal to Rs 18914.50 per month and the number of spare parts is **88.49≈89** spare parts. Therefore it would be better, if time interval for ordering of spares is made equal to 1.5 month instead of 1month. An annual saving to the tune of 16% could be achieved by following the revised time interval for spare parts ordering. The sensitivity analysis is also conducted at the end for the case study project-X. In this the three costs are varied within ±2% on both sides (lower and higher) of their initial values. The observation of sensitivity analysis is that Inventory ordering cost has the highest impact on the total cost rate. Variation in the backordering cost and holding cost hardly has any impact on the value of total cost rate (TC).

7. References

[1] Sarmiento, A. Rabelo, L. Lakkoju, R. Moraga, R., "Stability analysis of the supply chain by using neural networks and genetic algorithms", Proceedings of the winter Simulation Conference, pp: 1968-1976, 2007.

[2] Joines J.A., & Thoney, K, Kay M.G, "Supply chain multi-objective optimization", Proceedings of the 4th International Industrial Simulation Conference., Palermo, pp. 125-132, 2008.

[3] P. Radhakrishnan, V.M. Prasad, M.R. Gopalan, "Genetic Algorithm based inventory optimization Analysis in supply chain management", IEEE International Advance Computing Conference (IACC 2009) Patiala, India, 6-7 March 2009.

[4] MCTF, 2012. Airline Maintenance Cost: Executive Commentary - an Exclusive Benchmark Analysis (FY2010 Data) by IATA's Maintenance Cost Task Force.

[5] Jingyao Gu, Guoqing Zhang, Kevin W. Li, "Efficient aircraft spare parts inventory management under

demand uncertainty" Journal of Air Transport Management Issue-42 pp. 101-109, 2015.

[6] José Roberto do Rego, Marco Aurélio de Mesquita, " Spare parts inventory control: a literature review", Produção, v. 21, n. 4, out./dez., p. 656-666, 2011.

[7] Nataša Z. Kontrec, Gradimir V. MilovanoviT, Stefan R. PaniT, and Hranislav MiloševiT, "A Reliability-Based Approach to Non-repairable Spare Part Forecasting in Aircraft Maintenance System**",** Hindawi Publishing Corporation Mathematical Problems in Engineering Volume 2015.

[8] Ghobbar, A.A., Friend, C.H., "The material requirements planning system for aircraft maintenance and inventory control": a note. J. Air Transp. Manag.10, pp. 217-221, 2004.

[9] Maurizzio Faccio 2009-10, "Forecasting methods for spare parts Demand" PhD Thesis, Faculty of Engineering, Department of Technical and management of Industrial System, University of Padua, Italy, 2009-10.

[10] Hanke J.E., Reitsch A.G., "Business forecasting" (fourth edition), Needham Heights, MA: Allyn and Bacon, 1992.

[11] Sihong Peng, Nick Vayenas, "Maintainability Analysis of Underground Mining Equipment using Genetic Algorithms: Case Studies with an LHD Vehicle", Hindawi Publishing Corporation Journal of Mining Volume 2014.

[12] US Census Bureau, (Current Industrial Reports) Mining Machinery and Mineral Processing Equipment, U.S. Census Bureau, Suitland, Md, USA, 2009.

[13] Nishith Kumar Samal, Dilip Kumar Pratihar, " Joint optimization of preventive maintenance and spare parts inventory using genetic algorithms and particle swarm optimization algorithm", International Journal of System Assurance Engineering and Management, Vol-6, Issue-3, pp.-248-258, 2015.

[14] S. Godwin Barnabas, I. Ambrose Edward, S.Thandeeswaran, "Spare parts Inventory Model for Auto Mobile Sector using Genetic Algorithm", 3rd International Conference on Trends in Mechanical and Industrial Engineering (ICTMIE-2013), Kuala Lumpur (Malaysia). January 8-9, 2013.

[15] Abbas Barabadi, Javad Barabady, Tore Markeset, "Application of reliability models with covariates in spare part prediction and optimization- A case study", Reliability Engineering and System Safety, Vol-123, pp-1-7, 2014.

[16] Behzad Ghodrati, Uday Kumar, "Reliability and operating environment-based spare parts estimation approach", Journal of Quality in Maintenance Engineering, Vol. 11, No. 2, pp. 169-184, 2005.

[17] Chen F.L., Chen Y.C., "An investigation of forecasting critical spare parts requirement", World congress on computer science and information engineering, p. 225-230, 2009.

[18] Ghobbar A.A., Friend C.H., “Evaluation of forecasting methods for intermittent parts demand in the field of aviation: a predictive model”, Computers & Operation research, n.30, p.2097-2114, 2003.

[19] Ben-Daya M., Duffuaa S.O., Raouf A., Maintenance, modelling and optimization, Norwell, Massachusetts: Kluwer Academic Publisher, 2000.

[20] Croston J.D., "Forecasting and stock control for intermittent demands", Operational Research Quarterly, n.23, p.289-303, 1972.

[21] Syntetos A.A., Boylan J.E., "On the bias of intermittent demand estimates", International journal production economics, n.71, p. 457-466, 2001.

[22] Harris FW, "How many parts to make at once", Fact Mag Manag 10(2):135. doi:10.1.1/jpb001, 1913.

[23] Wilson RH, "A scientific routine for stock control", Harv Bus Rev 13:116, 1913.

[24] Jaber MY, Inventory management, non-classical views. CRC Press Taylor & Francis Group LLC, Boca Rato, 2009.

[25] Barlow RE, Proschan F, "Mathematical theory of reliability", Wiley, Hoboken, 1965.

[26] Pham H, "Handbook of reliability engineering", Springer, London, 2003.

[27] Nakagawa T, "Maintenance theory of reliability", Springer series in reliability engineering Springer, London, 2005.

[28] Wang H, Pham H, "Reliability and optimal maintenance", Springer series in reliability engineering Springer, London, 2006.

[29] Flowers AD, O'Neill JB II, "An application of classical inventory analysis to spare parts inventory", Interfaces 8(2):76, 1978.

[30] Kaio N, Osaki S, "Optimum ordering policies with lead time for an operating unit in preventive maintenance", IEEE Trans Reliab, Vol.-27, Issue (4), pp-270, 1978.

[31] Yamada S, Osaki S, "Optimum replacement policies for a system composed of components", IEEE Trans Reliab, Vol.-30, Issue (3), pp.-278, 1981.

[32] Acharya D, Nagabhushanam G, Alam SS, "Joint optimal block replacement and spare provisioning policy", IEEE Trans Reliab, Vol.-35, Issue (4), pp.-447, 1986.

[33] Chien YH, "Generalized spare ordering policies with allowable inventory time", Int J Syst Sci, Vol.-36, Issue (13), pp.-823, 2005.

[34] Ilgin MA, Tunali S, "Joint optimization of spare parts inventory and maintenance policies using genetic algorithms", Int J Adv Manuf Technol, Vol.-43, pp.-594, doi: 10.1007/s00170-006-0618-z, 2007.

[35] Gharbi A, Kenne JP, Beit M, "Optimal safety stocks and preventive maintenance periods in unreliable manufacturing systems", Int J Prod Econ, Vol.-107, pp.-422, 2007.

[36] Rausch M, Liao H, "Joint production and spare part inventory control strategy driven by condition based maintenance", IEEE Trans Reliab, Vol.-59, Issue (3), pp.-507, doi:10.1109/TR.2010.2055917, 2010.

[37] Chen JA, Chien YH, "Optimal spare ordering time for preventive replacement to maximize the cost effectiveness', Commun Stat—Theory Methods, Vol.-39, pp.-2410, doi: 10.1080/ 03610926.2010.484156, 2010.

[38] Xu CA, Zhao JM, Wang ZY, Guo RH, In: Proceedings of international conference on quality, reliability, risk, maintenance, and safety engineering (ICQR2MSE), Santa Barbara, California, USA, 2011.

[39] Basten RJI, van der Heijden MC, Schutten JMJ, "Joint optimization of level of repair analysis and spare parts stocks", Eur J Oper Res, Vol.-222,Issue (3), pp.-474, doi:10.1016/j.ejor.2012.05.045, 2012.

[40] Kurnaiti N, Yeh RH, Haridinuto, In: Proceedings of the institute of industrial engineers Asian conference, Santa Barbara, California, USA, pp 1353–1360, 2013.

[41] Chen L, Ye ZS, Xie M, "Joint maintenance and spare parts provisioning policy for k-out-of-n systems", Asia-Pac J Oper Res, Vol.-30, Issue (6), pp.-63, doi: 10.1142/S0217595913500231, 2013.

[42] Goldberg, David E., 'Genetic Algorithm in search, optimization and machine learning', Pearson Education (P) Ltd., Singapore, 1987.

[43] Mitchell Melanie, "An Introduction to Genetic Algorithms", A Bradford Book The MIT Press Cambridge, Massachusetts, London, England, Fifth printing, 1999.

[44] Cox, D.R., "Regression models and life-tables", Journal of the Royal Statistical Society, Vol. B34, pp. 187-220, 1972.

[45] http://ncl.gov.in/page.php?pid=53.

[46] http://www.mathworks.com/search/site_search.html?c%5 B%5D=entire_site&q=genetic+algorithm.