Stock Optimization of Spare Parts with Genetic Algorithm

Erkan Kiyak[a] Mehmet Yildirim[b] Adem Tuncer[c]

[a] *Institute of Natural and Applied Sciences, Kocaeli University, 41380 Kocaeli.*
[b] *Information Systems Engineering, Kocaeli University, 41380 Kocaeli.*
[c] *Computer Engineering Department, Yalova University, 77200 Yalova.*

Abstract

In this research, a new method is proposed for the optimization of warship spare parts stock with genetic algorithm. Warships should fulfill her duties in all circumstances. Considering the warships have more than a hundred thousand unique parts, it is a very hard problem to decide which spare parts should be stocked at warehouse aiming to use in case of failure. In this study, genetic algorithm that is a heuristic optimization method is used to solve this problem. The demand quantity, the criticality and the cost of parts is used for optimization. A genetic algorithm with very long chromosome is used, i.e. over 1000 genes in one chromosome. The outputs of the method is analyzed and compared with the Price Sensitive 0.5 FLSIP+ model, which is widely used over navies, and came to a conclusion that the proposed method is better.

1 Introduction

Warships are non-profit and mission focused organizations. They must cruise for a long period to fulfill their missions. It is a high probability to have a system failure during her cruises. Some of the failures are simple enough for ship's staff to repair, and some of them are complex failures that reparation can be fixed only at dockyards. Repairs that ship's crews fixed are very valuable because they support the main goals of warships. Otherwise, the ship should go to the dockyard, sometimes in tow, that means abolishment or delay of the mission.

It's a necessity to have the spare parts in the warehouse of warship for the ship's crew to fix the failure. A frigate may have hundreds of systems on her, and these systems may include more than one hundred thousand parts. It's clear that you can not stock a spare of all parts. So, the big problem is which parts will be stocked at warehouse as a spare part.

Many researches have been done related to stock models of spare parts used in navies. [1-3]. Navies of the world, especially the United States' Navy created and improved many methods since 1950s to handle this problem. The most up to date method used is Price Sensitive 0.5 FLSIP+. This method focuses on demand quantity and excludes a spare part which has the demand quantity less than a threshold even though it is very important for the ship. On the other hand, a part that has a low cost can be carried on board even though it has no importance for the ship. Therefore, a heuristic algorithm should be used instead of a method which decides according to crisp parameter values.

Genetic algorithm is a heuristic optimization method that used increasingly in so many areas. Many problems, which are complex or impossible to solve with deterministic methods, can be solved by genetic algorithm. In this study, a genetic algorithm is used to answer the problem of spare parts optimization, which should be stocked on a warship. The outputs of spare parts stock list acquired from the genetic algorithm is analyzed and compared with the solutions of present navy methods, according to the demand quantity, criticality and cost of the spare parts.

2 Price Sensitive 0.5 FLSIP+ Model

The raw data size of all spare parts is 74,601. This information is gathered from Coordinated Shipboard Allowance List (COSAL) data of a warship. In this data, ID is the serial numbers of the parts. P is the unit price. Military essential code (MEC) represents the criticality or importance of a part in the operation of equipment or system. Total available quantity (TP) is the quantity of a part which is already installed on board. Minimum replacement unit (MRU) is the minimum quantity that should be replaced when a failure occurs. Best replacement factor (BRF) shows the usage rate. It is the actual usage reported by fleet. By multiplying TP and BRF, estimated annual demand quantity is obtained.

Price Sensitive 0.5 FLSIP+ model [4], which is abbreviated as PS 0.5F+, never takes into account the estimated annual demand quantity that is lower than 0.5 while computing the spare parts allowance list. In other words, estimated annual demand quantity should be 0.5 or higher to be considered in generating a spare parts allowance list that should be carried on board.

The warships should survive without aid for a 90-day period. Therefore, all the logistic stock preparation is fulfilled for this period. First of all, usage rate should be obtained by the equation below.

$$UR = \frac{TP.BRF}{4} \tag{1}$$

Where; UR is usage rate. It is an estimate of how often a part will be needed in each 90-day period. The 4 in denominator determines the expected usage for a 90-day period, which is the established stocking level duration. PS 0.5F+ model uses below conditions to decide whether a part will be selected as a spare part or not.

- UR >= 1 condition: If the usage rate (UR) of a part is equal to or higher 4 in a year, that spare part is determined as on board repair part (OBRP) and carried on board, without considering its cost. This type of spare parts called as demand-based parts.
- Cost < 1000$ and 0.5 < UR < 4 condition: If the usage rate (UR) of a part is between 0.5 and 4 in a year, that spare part is candidate for OBRP. If the candidate part is critical for the ship it is considered as OBRP, and should be carried on board. This type of spare parts called as insurance-based parts.
- Cost >= 1000$ and UR < 4 condition: If the usage rate (UR) of a part is equal to or less than 4 in a year, that spare part is excluded from OBRP and never carried on board.
- Exceptions: There are certain Technical Overrides (TORs) and underrides that can cause a part to be carried or not carried regardless of the value of the UR. In addition, Planned Maintenance Requirement (PMR) for 90-day usage will also override the allowance computation. TORs and PMR are out of the scope of this research.

3 Genetic Algorithm Parameters

Genetic algorithm is an optimization method that uses stochastic algorithms. The first step in GA is to generate an initial population, which is randomly generated. The potential solutions of a problem are encoded as chromosomes, which form a population [5]. The second step is to determine fitness of chromosomes in the population. A chromosome represents a candidate solution for the problem. The third step is a selection of better chromosomes according to fitness values. Then reproduction takes place, which consists of crossover and mutation operators. The algorithm is repeated until an optimal solution is found.

Generally, crossover combines the features of two parent chromosomes to form two offspring. All candidate chromosomes in the population are subjected to the random mutation after the crossover operation. This is a random small change in a gene applied uniformly to all genes of chromosomes with a probability of mutation rate. Mutation operation increases the diversity of the population and avoids the premature convergence [6].

The most important task in the GA is to compose an objective function. The objective function given in Equation 2 is introduced in this study for determination of spare parts that should be carried on the ship. In this process, the criteria taken into accounts are the unit price, criticality, demand quantity, maximum replacement unit of parts and total available quantity on board.

$$Z = \sum_{i=1}^{n} \left(\frac{P_i}{\sqrt[3]{MEC_i}} \right) \left(\left\lceil \frac{TP_i.BRF_i}{MRU_i} \right\rceil .MRU_i \right) \tag{2}$$

Where; Z is the objective function value and i is the *Id* of a spare part.

The roulette-wheel selection method is used for the determination of parents who will be put into mating pool. Besides, elitism is used to ensure that the good solutions are transported to the next generations. Elitism prevents the loss of properties of good solutions during the crossover and mutation operations.

Many pre-experiments were conducted to determine the parameters of GA. Mutation rate was determined as 0.00075, crossover rate was taken as 1, 3-point crossover was founded as the most convenient crossover type, the population size was obtained as 300, and 1000 genes were consisted in one chromosome.

4 Case Studies

When the existing PS 0.5F+ model is operated based on the conditions given in Section 2, total of 5,529 parts are selected by the model (see Table 1). Those consist of 1,619 demand based parts that have the demand quantity higher than 4.0, and 3,910 insurance based parts that have the demand quantity between 0.5 and 4.0 in a year. The total cost of spare parts selected by PS 0.5F+ model is 952,551.34$.

We aim that the total quantity and cost of parts, which are selected as on board spare parts, will be lowered by GA. While optimizing with GA, a threshold value of demand quantity is accepted as 0.1. Most of these low valued spare parts don't have any chance to be selected by the genetic algorithm. When this filtration is applied to the raw data size of all spare parts, 74,601 records degrade to 16,186 records. 58,415 records have an estimated annual demand quantity less than 0.1 and excluded from the raw data. In addition, the size of the on board list is just taken as 1,000 so the chromosome length of the genetic algorithm is defined as 1,000. The difference in cost and quantity of parts selected by both methods can be seen on the Table 1. The comparison of total costs and quantities of both method shows that GA is advantageous as expected.

Table 1. Total costs and quantities acquired by PS 0.5F+ model and GA.

	PS 0.5F+	GA
Cost ($)	952,551.34	133,471.33
Quantity	5,529	1,000

4.1. Comparison of Results According to Quantities

The 5,529 outcomes acquired by the PS 0.5F+ model and the 1,000 outcomes acquired by the GA are compared according to the spare parts quantities and comparison results are given in Table 2. Striking results are given below.

Because the PS 0.5F+ model does not deal with the parts that have a demand quantity less than 0.5, 422 parts that have a demand quantity between 0.1 and 0.5 is selected only by GA. 82 parts which have a demand quantity between 0.5 and 4.0 are selected by GA even though not selected by PS 0.5F+ model. The selection criteria for the GA are unit price, criticality and demand quantity of the part as formulated in objective function. Therefore, the reason why a part selected by GA but not selected by PS 0.5F+ model is due to low cost or high criticality of the part. The ratio of parts selected by GA that has a demand quantity of 4.0 or greater is 23.5% (235/1,000). Even though the PS 0.5F+ model selects all the parts have a demand quantity of 4.0 or greater, the selection ratio for the PS 0.5F+ model is only 29.3% (1619/5,529). The ratio of selected parts that have a demand quantity between 0.5 and 4.0 for PS 0.5F+ model is 70.7% (3,910/5,529), while the genetic algorithm model has a ratio of 34.3% (343/1,000).

Table 2. Quantities of spare parts selected by PS 0.5F+ model and GA.

Quantity of parts selected by	Demand quantity			Total
	between 0.1 -0.5	between 0.5 -4.0	higher than 4.0	
only GA	422	82	0	504
both PS 0.5F+ and GA	0	261	235	496
only PS 0.5F+	0	3,649	1,384	5,033
neither PS 0.5F+ nor GA	9,189	964	0	10,153
Total	9,611	4,956	1,619	16,186

4.2. Comparison of Results According to Mean Costs

Outcomes acquired by both the PS 0.5F+ model and the GA are compared according to the mean costs of spare parts and comparison results are given in Table 3. Striking results are given below.

The mean cost of the 82 parts, which have a demand quantity between 0.5 and 4.0, and selected by only GA, is just 0.76$. On the other hand, the mean cost of 3,649 parts which have a demand quantity between 0.5 and 4.0, and selected by only PS 0.5F+ model is 44.20$. This enormous mean cost shows that GA is much better if the costs of parts are considered. The mean cost of 235 parts, which have a demand quantity more than 4.0, selected by both methods is just 2.44$. On the other hand, the mean cost of 1,384 parts selected by only PS 0.5F+ model is 25.51$. This mean cost shows again that GA is much better.

Table 3. Mean costs of spare parts selected by PS 0.5F+ model and GA.

Quantity of parts selected by	Demand quantity		
	between 0.1 -0.5	between 0.5 -4.0	higher than 4.0
only GA	0.43	0.76	0.00
both PS 0.5F+ and GA	0.00	0.68	2.44
only PS 0.5F+	0.00	44.20	25.51
neither PS 0.5F+ nor GA	545.52	1,305.68	0.00

4.3. Comparison of Results According to Criticality

There are four criticality degrees (1, 3, 5 and 7), and as the criticality degree decreases, the criticality or importance of a part increases. For the both methods, quantities of the selected parts according to the criticality degrees are given in Table 4. The aim of this comparison is to make a comment about the influence of criticality. Striking results are given below.

When the parts that have a demand quantity between 0.1 and 0.5 are inspected, the criticality degree of 403 of 422 parts selected by GA is either 1 or 3. The criticality degree 7 means that the part is the least critical. When the parts, which have a demand quantity between 0.5 and 4.0 and have a criticality degree 7, are analyzed the quantity of selected parts are determined as 99. The 8 (8%) of them are selected by both methods, 88 (88.8%) of them are selected by only PS 0.5F+ model, and none of them is selected by only GA. The criticality degree 3 means that the part has major criticality for the system. The 79 of 806 parts, which have criticality degree 3 and demand quantity between 0.5 and 4.0, are selected by only GA. None of these 806 parts is selected by PS 0.5 F+ model. This shows the deficiency of PS 0.5 F+ model and the superiority of GA for selecting spare parts.

Table 4. Criticalities of spare parts selected by PS 0.5F+ model and GA.

Quantity of parts selected by	Criticality degree	Demand Quantity		Demand Quantity		Demand Quantity		Total	
		0.1-0.5	Total	0.5-4.0	Total	4.0-?	Total		
only GA	1	300	422	2	82	0	0	302	504
	3	103		79		0		182	
	5	1		1		0		2	
	7	18		0		0		18	
both PS 0.5F+ and GA	1	0	0	252	261	177	235	429	496
	3	0		0		51		51	
	5	0		1		0		1	
	7	0		8		7		15	
only PS 0.5F+	1	0	0	3,536	3,649	1,154	1,384	4,690	5,033
	3	0		0		204		204	
	5	0		25		3		28	
	7	0		88		23		111	
neither PS 0.5F+ nor GA	1	7,608	9,344	234	964	0	0	7,842	10,153
	3	1,328		727		0		2,055	
	5	53		0		0		53	
	7	200		3		0		203	

5 Conclusion

It is necessary to have the spare parts in stock of warship for fixing the failure during her duties. Since a ship has hundred thousand unique parts, it is difficult to decide which spare parts should be stocked on board. In this study, GA was used to solve this problem. The raw data of 74,601 spare parts were gathered from COSAL data of a warship. The spare part list derived from the GA was compared with list derived from the PS 0.5 F+ model according to the quantities, costs and criticalities of the selected spare parts.

All the comparisons show clearly that the spare parts allowance list that should be carried on board, which is determined by the GA, is much more convenient and price sensitive than the list of PS 0.5F+ model. Because the selection criteria for a spare part were unit cost, criticality and demand quantity as formulated in the objective function, GA selected the critical, cheap and more demanded spare parts. However, the most deficiency of the PS 0.5F+ model was the excluding of parts that have a demand quantity lower than 0.5 and including all parts that have a demand quantity higher than 4.0 without looking any other properties like cost and criticality.

References

[1]. M.A. Eggenberger. Implementation of Reduced Shipboard Allowance Levels Reapplication Savings Analysis. *MS. dissertation, Dept. Sys. Management, Naval Postgraduate School,* Monterey, CA, 1994.

[2]. M.D. Pawley. A Comparative Efficiency Analysis of the Point Five FLSIP Plus COSAL Inventory Model. MS. dissertation, Dept. Sys. Management, Naval Postgraduate School, Monterey, CA, 1995.

[3]. C.B. Penrose. Data Requirements for Availability Based Sparing in the US Marine Corps. MS. dissertation, Dept. Sys. Management, Naval Postgraduate School, Monterey, CA, 1998.

[4]. Coordinated Shipboard Allowance List (COSAL). Use and Maintenance Manual, Naval Inventory Control Point Internal Instruction 4441.170B, Philadelphia, PA, Government Printing Office.

[5]. J.C. Mohanta, D.R. Parhi and S.K. Patel. Path planning strategy for autonomous mobile robot navigation using Petri-GA optimization. Comput. Electr. Eng., 37:1058–1070, 2011.

[6]. A. Tuncer and M. Yildirim. Dynamic path planning of mobile robots with improved genetic algorithm. Comput. Electr. Eng., 38:1564-1572, 2012.