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Genetic Algorithm Based Framework For Managing Medical Equipment Replacement

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Abstract— Planning of medical equipment management is a complex issue. Many dimensions should be considered in this process. The quality level of the provided service and costs policies are the most influential ones. Recently, hospitals are interested in minimizing the expenditures by optimizing the planning of all activities. Therefore, proper identification of the framework of medical equipment management including which, what, and how is essential. The aim of the paper was to optimize planning of disposal or replacement in addition to review maintenance activity. The management process was performed using genetic algorithm. It is employed as an optimization tool to guide and differentiate both activities. Medical imaging equipment was chosen for this purpose. According to the output of genetic algorithm, adopting maintenance strategy or disposal was selected for each equipment. Key Performance Indicators were suggested for reviewing the adopted maintenance strategies to enhance the overall performance. The model has been applied on 20 pieces of medical imaging equipment including four modalities. Outcomes revealed the robustness of the model in support decision making. Indeed, genetic algorithm proves its ability to maximize the number of equipment require reviewing maintenance strategy, and simultaneously minimize the number of equipment requires disposal effectively.

Index Terms— Medical equipment, Maintenance, Disposal, Replacement, Genetic algorithm, Key performance indicator, Hospital.

1 Introduction

MEDICAL equipment is a stone corner in healthcare facilities. Generally, medical technology provides a diagnosis for the clinical signs, identify the cause of abnormal, and risk conditions. It helps the restoration of body function by improving or replacement. In addition, the severity and duration of the disease are expected to scale down with the upgrading in medical technology [1]. Due to this importance, hospitals allocate a large portion of their resources for purchasing and managing assets. They are regularly facing increasing demands of access to healthcare services, newer medical technology and face challenges to deal with and manage the old and new generation of inventory at the same time. Therefore, a proper management plan is required [2]. Different studies were conducted on management of medical equipment using various approaches. However, in developing countries the situation seems scary. According to the World Health Organization (WHO), approximately 50% of medical devices in the developing countries are not in a good investment [3].

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In this case, most of decisions are made subjectively without regarding the real circumstances of the equipment. Therefore, adequate planning should be followed based on objective criteria.

Indeed, such forms of improper management process are time and resources consuming, leading to influential impact on healthcare delivery. To avoid such fatal mistakes, decisions should be made relied on realistic models considering objective technical and financial criteria. In literature, one study was conducted to manage medical equipment centrally by using Internet of Things (IoT) [4]. Central management of medical equipment including lease management, routine management, statistical analysis, emergency management, and regulations formulation. The proposed system was developed on Wi-Fi data transmission technology. Different functional sensors were embedded in medical devices to provide precise location and status information. The system has been applied on emergency medical equipment such as defibrillators and ventilators.

In another study, Analytical Hierarchy Process (AHP) was utilized in medical equipment maintenance through 3 types; corrective maintenance, time-based maintenance, and condition-based maintenance [5]. The main criteria were age, EM number, mission criticality, FMEA RPN, failure consequence, and technology complexity. In addition, other sub-criteria were utilized. The model was tested on 40 pieces of medical imaging equipment belong to 9 hospitals in Egypt. Another relevant study was conducted by *Masmoudi et al*. [6], in which, procedure for maintenance of medical equipment was adopted. The goal was to select appropriate maintenance strategy, insourcing/outsourcing, and selection of contract type based on multi-level criteria. The procedure was developed based on four steps; calculating the equipment's criticality, insourcing maintenance service workload, identifying the maintenance strategy, and finally outsourcing and contracting. A fuzzy approach was employed by *Mummolo et al*. [7]. In this paper, a fuzzy inference model was proposed to recognize a list of medical devices require replacement. Linguistic and quantitative factors were identified to measure their influence on the replacement decision.

In the developing countries, decision making in maintenance and disposal stages is usually carried out without forward planning. Therefore, the aim of this study was to develop a model that separates medical equipment which requires disposal from the nominated list of maintenance. In particular, medical imaging equipment is considered due to its highly expenditures in addition to its criticality.

The paper is organized as follows. The adopted methodology is presented in details in section 2. Validation of the model is applied in section 3, in which results and discussion are introduced. The last section concludes the study and suggests future work

2 METHODOLOGY

Optimizing medical equipment for disposal or maintenance based on its conditions is a critical issue that should be highlighted. A range of optimization tools is inspired by nature such as ant colony algorithm, bee colony algorithm, and genetic algorithm. Among these algorithms, genetic algorithm (GA) is commonly used. GA is a general purpose metaheuristic framework that can be applied for various optimization problems. Indeed, GA mimics some features of natural evolution; potential solutions are provided for a number of populations. The solution is a search space of the optimization problem. Each solution presents an alternative in a form of genetic expression [8]. In fact, GA simulates the principle of Darwin "the survival of the fittest" over consecutive generations by applying genetic operators to find out the best solutions [9].

Two genetic operators are used in GA; crossover and mutation. In crossover, two parents are recombined in order to produce new offspring; meanwhile mutation is an error existing in typing the gene code to add a diversity to the populations. Reproduction or selections of populations is commonly done using Roulette wheel operator [10]. The process of generating new populations is repeated until maximum number of iterations are fulfilled and/or specific criteria are met. In application, GA construction involves three steps; objective function formulation, developing the algorithm, and tuning of parameters [11].

Medical imaging equipment is an expensive asset in terms of acquisition and management. Moreover, financing resource is often restricted especially in the developing countries. Therefore, hospitals should assign specific strategies for this type of equipment. In this study, a new technology management strategy is adopted using GA. Based on cost-effectiveness analysis outcomes, a list of medical imaging equipment needed to be optimized to be either scrapped/replaced or maintained. Further, a set of Key Performance Indicators (KPIs) is recommended to guide selection of appropriate maintenance strategy. The overall process using GA is depicted in Fig. 1 and explained in the following subsections.

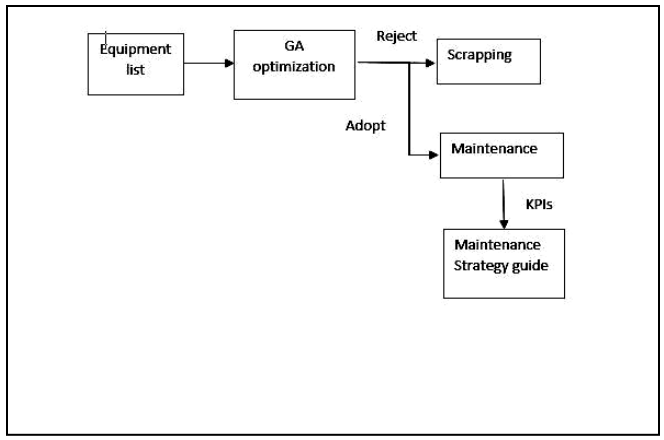

Fig. 1 Overall management process using GA including scrapping and maintenance

2.1 Selection of Equipment

A list of medical imaging equipment is analyzed based on cost-effectiveness analysis. As a result, a portion of equipment list requires further analysis to be adopted or rejected. The list involves 20 medical imaging equipment incorporating MRI, CT, Digital X-ray, and Ultrasound at two hospitals in KSA. Thus, the input of genetic algorithm model will be the 20 medical imaging equipment.

2.2 Genetic Algorithm

Genetic algorithm is used to optimize the list of equipment employing a combination of influential indicators and criteria. The purpose is to make a informed decision which should be disposed and which should be remained based on its real status. The proposed indicators are important factor, expected remaining useful life, and performance rate. Which in turn lead to the calculation of the weighted profit for each device. The importance factor was calculated based on the cost of acquisition where it corresponds to every million or less with a value of 0.1. In this stage, A total of 6 criteria was suggested to be employed to evaluate device performance rate. Criteria are *utilization rate, alternative devices, availability of the device, downtime ratio, type of maintenance, and effectiveness value*. By using these criteria, each piece of imaging equipment is evaluated and performance rate is given using (1). In this formula, S is the performance rate of equipment, C is a criterion, j is a criterion index, and n is the number of criteria. Table 1 illustrates the proposed criteria with their scores. As shown from Table 1, the score ranges from 33 as a maximum to 6 as a minimum.

$$S = \sum_{i=1}^{n} C_i \qquad (1)$$

TABLE 1
CRITERIA DESCRIPTION WITH SCALE OF SCORES

Criterion	Description	Threshold	Score
Utilization rate	Working hours / available hours	Ratio >15% of average	6
		Ratio ≥ average by 15%	3
		Ratio < average	1
Alternative devices	Existence of back up devices	No alternative	3
		One alternative	2
		More than one device	1
Device availability	Working hours per day	24 hours	3
		16 hours	2
		8 hours	1
Effectiveness value	Of current state	according to the average of modality	9 3 1
Service type	Maintenance contract type	Partial contract	1
		Full contract	3
Downtime	Out of service days in a year	# of days ≥ 30	1
		15≤ # of days <30	2
		# of days <15	3

2.2.1 Objective Function Formulation

According to the assumption of this paper, we need to maximize the number of maintained medical imaging devices and simultaneously to maximize the total profits gained with minimizing the number of disposed devices. In other words, the goal is to maximize maintained equipment and to minimize scrapped equipment effectively. Taking into account weighted profits, maintenance costs and the available total maintenance budget, the objective function is formulated as in (2),(3) and (4) respectively.

$$R(u) = \alpha . objective\_1(u) + (1 - \alpha). objective\_2(u) \qquad (2)$$

$$objective\_1(u^n) = \sum_{i=1}^{i=N} u_i \qquad (3)$$

$$objective\_2(u^n) = \sum_{i=1}^{i=N} p_i u_i \qquad (4)$$

Subjected to:

$$\sum_{i=1}^{i=N} w_i u_i \leq 70\%\ of\ total\ cost\ \ \forall\ n \epsilon\ (1,2,3 \ldots \ldots N)$$

Where,
objective_1 is number of devices and ***objective_2*** is Total weighted profits. u denotes the number of devices as variable. w_i is weighted maintenance cost for ith product. u_i denotes the state of the ith device. p_i denotes profit value for ith device.
The Alpha (α) in the objective function considers as a weighting function where α and $(\alpha - 1)$ denotes the weighted valued for objective_1 and objective_2 respectively. The value of α = 0.5 means the maximum number of devices and the maximum weighted profits are obtaining equal importance. Values over that for α means the maximum number of devices are more important than maximum weighted profits gained, and values below that means the maximum number of devices are less important and vice versa. In this paper, the values of α that are used, range from 0.1 to 1.0 with an interval of 0.1. By simulating and testing different Alpha values, the optimal weights for objective_1 and objective_2 were obtained [15]. From the figures 2, 3 and 4, it can be observed that as the value of α is increase the values of optimized objective function $R(u)$ decreases. It can be seen that in *case 1*, the maximum fitness value is obtained. From Fig 4 it can be depicted that in case 1 The value of α is *0.1*. Again, From Fig 3 it can be seen that the weighed value for objective 2 is *0.9* in case 1.

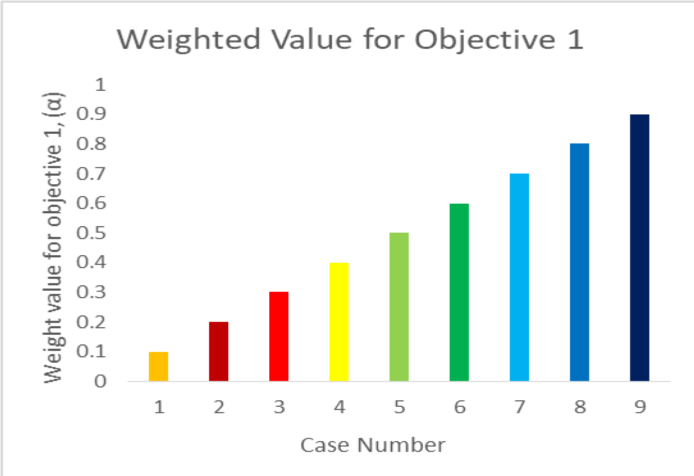

Fig. 3 Weighted value for objective_1

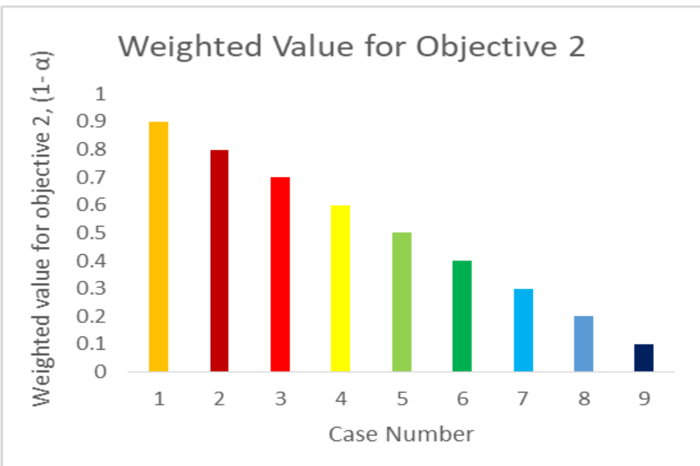

Fig. 4 Weighted value for objective_2

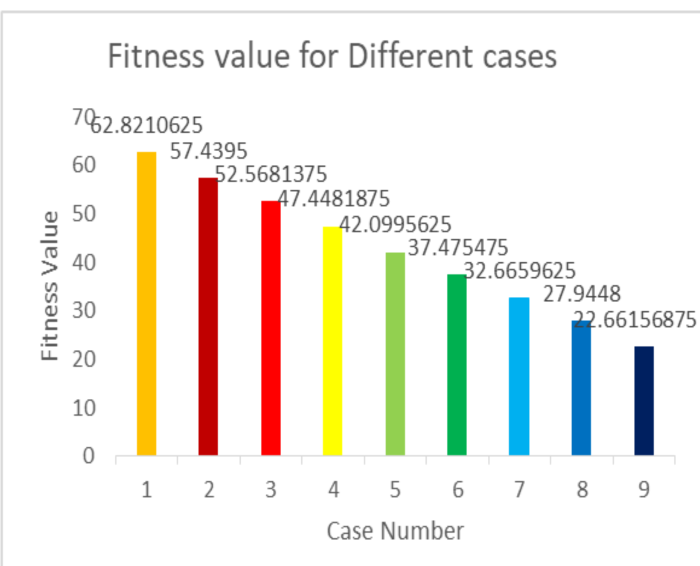

Fig. 4 Fitness value for different cases

2.2.2 Algorithm Development

In this section, general procedure for establishing GA algorithm is adopted. The algorithm starts usually with initial selection of population. The new generations are produced by selecting the fittest solutions by evaluating the values of the objective function. Subsequently, crossover and mutation operators are applied to generate new offspring. The sequence is repeated until acceptable solutions are found or specific criteria are met. GA steps are presented below:

1- Parameters Initialization (No. of devices, values, weights, and maintenance budget);
2- Creating the first generation;
3-Defining GA parameters (selection, mutation, and crossover);
4- Create new population;
5- Checking the stop criteria
6- Evaluate the fitness function for each individual solution;
7- GA Selection;
8- GA Crossover;
9- GA Mutation;
10- Stimulate new generation;
Repeat steps from 6 to 10 until getting the best solution or met the stop criteria.

2.2.3 Parameter tuning

Development of GA algorithm is characterized by random calculations. In this context, GA calculations are affected by parameters tuning. Number of populations, number of iterations, crossover probability, and mutation probability are randomly chosen to run the algorithm as shown in Table 2. In application, different combinations of these parameters are selected to find out the best solutions.

TABLE 2
CRITERIA DESCRIPTION WITH SCALE OF SCORES

Populations	Iterations	Crossover probability	Mutation probability
40	100	0.4	0.1
50	200	0.5	0.2
60	300	0.6	0.3
70	400	**0.7**	**0.4**
80	500	0.8	0.5

3 RESULTS AND DISCUSSION

We have 20 pieces of medical imaging equipment belong to two hospitals in KSA require a decision-making. The modalities are MRI, CT, Ultrasound, and X-Ray. Hence, input of the algorithm is 20 devices with their parameters. As stated previously, solutions of the GA are calculated with different trails of random parameters. In running the algorithm, different combinations of the parameters are set. Therefore, the algorithm is repeated 16 times with every combination to optimize the parameters, resulting in more than 2000 simulations for total parameter tuning process. Taking into account, available total maintenance budget is assumed 2,220946 SAR. As we have five combinations of the parameters, so the best solutions are indicated in term of the mean. Initial arrangement is to use dissimilar preliminary populations with diverse iterations to get the optimal numbers of populations and iterations. From Table 2 based on the maximum average fitness value, crossover probability (P_c) = 0.7 and mutation probability (P_m) = 0.4 is selected for next experiment. Figure 5 depicts different combinations with the best solutions. It is noticed in figure 2 that optimal solutions are obtained at **90** populations and **400** iterations.

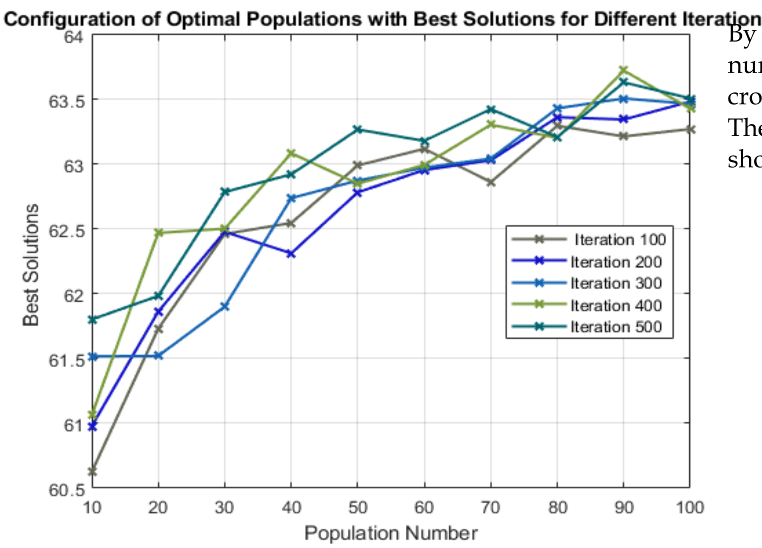

Fig. 5 Configuration of Optimal Populations with Best Solutions for Different Iterations using P_c = 0.7 and P_m= 0.4

The next step is to run the algorithm with number of populations equals 90 and number of iterations equals 400. The outcomes are to find optimum values of P_c and P_m of the algorithm. The same procedure is repeated; outputs are expressed in terms of the mean number of solutions. The different combinations are presented in Fig. 10 and Table 4.11. Results have yielded that the best solutions are achieved with P_c = 0.3 and P_m= 0.1

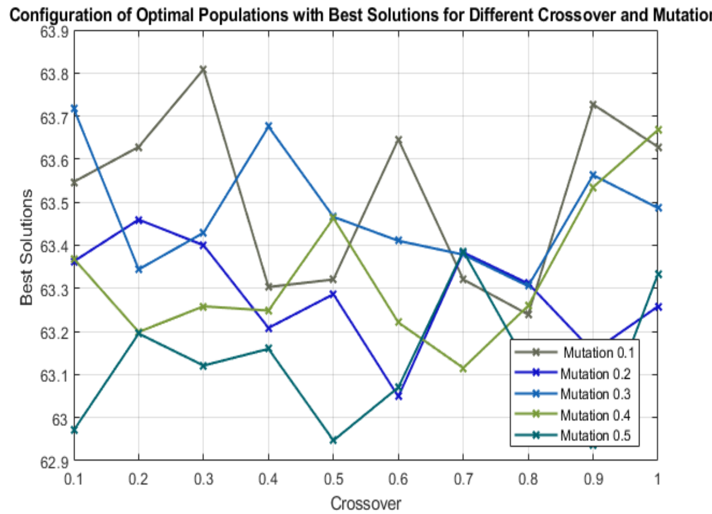

Fig. 6 Tuning of Best Solutions along Different Crossover Rates with Mutation Rates 0.1, 0.2, 0.3, 0.4 and 0.5

By scheduling the GA parameters, selection is as follows; number of populations is 90, number of iterations is 400, crossover probability is 0.3, and mutation probability is 0.1. The program was run twice and obtained same result. Fig. 7 shows the convergence curve after tuning the GA parameters.

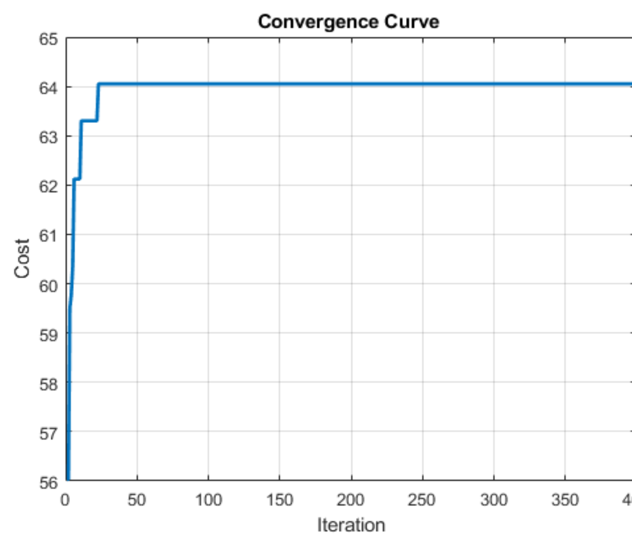

Fig. 7 Convergence Curve

The input dataset to the GA are summarized in Table 3 with the weighted benefits (p_i) and maintenance cost (w_i) are identified for each device. It is worthy to note that the total maintenance cost for these devices is 3,172,780 SAR while the assumption of the available maintenance budget is only 70% of the total required cost i.e. W= 2,220,946 SAR. This will make a savings of 951,834 SAR.

TABLE 3

INPUT DATASET TO GA WITH WEIGHTED BENEFITS (p_i) AND MAINTENANCE COST (w_i)

Index(i)	Device name (xi)	Maintenance cost -SAR (w_i)	Performance Rate	Weighted benefits (p_i)
1	D2	70000	10	0.833
2	D3	70000	10	0.833
3	D4	70000	10	0.833
4	D7	70000	10	1.167
5	D8	70000	24	2.8
6	D11	3360	15	1
7	D12	3360	18	1.35
8	D13	66000	24	2
9	D14	66000	16	1.333
10	D16	216000	30	8.75
11	D18	240000	18	9
12	D19	640000	24	7
13	D20	3360	16	1.2
14	D28	490000	22	0.55
15	D29	112500	27	10.8
16	D32	183600	14	7
17	D34	183600	23	9.583
18	D35	5000	31	9.042
19	D36	120000	8	0.2
20	D39	70000	7	0

In this work, in order to review the adopted maintenance strategy for those devices, Key Performance Indicators (KPIs) guide could be a beneficial tool. The GA optimization is applied on 20 medical imaging devices as input. The maximum number of best solutions obtained is 13 devices with a total maintenance cost of 2,216,780 SAR. Thus, we have 13 devices require reviewing their maintenance strategy and this will maintain saving of 970,320 SAR. On the other side, we have seven devices require to be disposed. Results of the GA are depicted in Table 4 in terms of device name, GA results and the decision.

TABLE 4

RESULTS OF THE GA INDICATING IMAGING EQUIPMENT DECISION

No	Imaging equipment	GA result	Device name (xi)	Decision
1	DIGITAL X-RAY (1)	0	D2	Disposal
2	DIGITAL X-RAY (2)	0	D3	Disposal
3	DIGITAL X-RAY (3)	0	D4	Disposal
4	MOBILE X-RAY (1)	0	D7	Disposal
5	MOBILE X-RAY (2)	1	D8	Maintenance strategy
6	US (1)	1	D11	Maintenance strategy
7	US (2)	1	D12	Maintenance strategy
8	MOBILE X-RAY (3)	1	D13	Maintenance strategy
9	MOBILE X-RAY (4)	0	D14	Disposal
10	CT 128 SLICES (1)	1	D16	Maintenance strategy
11	MRI 3T (1)	1	D18	Maintenance strategy
12	CT 128 SLICES (2)	1	D19	Maintenance strategy
13	US (3)	1	D20	Maintenance strategy
14	CT SCAN 32 SLICES	0	D28	Disposal
15	CT 64 SLICES (1)	1	D29	Maintenance strategy
16	MRI 3T (2)	1	D32	Maintenance strategy
17	CT 128 SLICE (3)	1	D34	Maintenance strategy
18	CT 64 SLICE (2)	1	D35	Maintenance strategy
19	US (4)	1	D36	Maintenance strategy
20	DIGITAL X-RAY (4)	0	D39	Disposal

4 CONCLUSION

Due to the impact of medical equipment management on healthcare delivery, a robust model was developed to enhance the management process. Genetic algorithm was proposed for this goal. In this paper, the author considered a set of medical imaging equipment because of its criticality in diseases diagnosis. Moreover, they are one of highly cost assets in hospitals. The algorithm was built based on technical and financial criteria. The aim was to optimize the list of equipment regarding their actual status to make a decision. The decision is either to adopt a new maintenance strategy or to scrap the equipment. The algorithm proves its robustness by correctly differentiating the both cases. In fact, a beneficial impact of any medical device could be improved if we adopt a maintenance strategy that reflects its real need. Therefore, the paper highlights the importance of reviewing the adopted maintenance modality, particularly for medical imaging equipment. In conclusion, using proper KPIs could be helpful. Further, a decision of disposal or replacement of medical imaging equipment is not easy to make. It should be considered as an evidence – based approach. Therefore, the GA model presents a new objective framework that could guide the decision makers in healthcare facilities. Moreover, the paper provides a guide to plan for budgeting allocation in case of adopting new maintenance strategy or even for substituting the disposed equipment. Thus, the work highlighted the impact of existence of a detailed history of medical devices in the management process. Also, the model could be generalized for other categories of medical equipment.

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