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A COMPARATIVE ANALYSIS OF METAHEURISTIC MAINTENANCE OPTIMIZATION OF REFUSE COLLECTION VEHICLES USING THE TAGUCHI EXPERIMENTAL DESIGN

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Summary

In this paper, a comparative analysis of the metaheuristic maintenance optimization of refuse collection vehicles (RCV) using the Taguchi experimental design is presented based on a RCV model as a multi-state degradation system with two dependent subsystems. The model which is based on a probabilistic approach includes two stochastic degradation processes, a random failure process and a set of maintenance actions and their effects. The optimal values of the mean time to preventive maintenance are determined by maximizing the availability of the complete system and by minimizing total costs. In order to solve the real life problem of the multi-objective optimization of RCV maintenance, three different metaheuristic optimization algorithms were used: a real coded genetic algorithm, an improved harmony search algorithm and simulated annealing. Each algorithm has parameters that need to be accurately calibrated to ensure the best performance. For this purpose, calibration was applied to the parameters by means of the Taguchi method. Finally, the optimal values of the mean time to minimal preventive maintenance of RCVs are obtained and computational results of the three optimization algorithms are compared.

Key words: *maintenance optimization, refuse collection vehicles, metaheuristics, Taguchi method*

1. Introduction

A very important segment in the life-cycle of a system is its maintenance process. The theory of engineering system maintenance is widely accepted as a discipline in the sense of providing an objective basis for solving system failure problems. The task of keeping the work equipment functional consists of maintaining its operation and its ability to perform on a desired level. Today, it is no longer sufficient to maintain the highest possible availability of a complex system by repairing it after a failure, but it is necessary to duly plan preventive activities in order to avoid failures and risks to the safety of the system and environment on the one hand and to reduce the cost of maintenance on the other [12].

In principle, problems of improving system reliability/availability and of reducing operation and maintenance costs have been studied for many years by using probabilistic models and the theory of Markov process. Thirty years ago, Sim and Endrenyi [25] obtained the optimal value of the mean time to minimal preventive maintenance by minimizing the unavailability of the device. They used a Markov model for repairable, continuously degrading components subjected to random and degradation failures. In a similar model, Chan and Asgarpoor [1] obtained the optimal value of the mean time to preventive maintenance by maximizing the availability of single components with respect to the mean time to minimal preventive maintenance. Also, Welte et al. [29] presented a model which can be used for maintenance optimization by minimizing operational total costs for different inspection and renewal strategies. Excellent literature reviews related to optimal maintenance policies for repairable components are given in [28, 7]. Further, paper [20] represents our previous work in this field where we presented three different models for both availability and cost optimization which include a stochastic degradation process, random failures and a set of maintenance actions and their effects. The common attribute in these papers was the assumption that the analyzed object was a single unit.

In recent years, the interest in multi-component maintenance models has been growing [5, 10, 11] because the application of the existing optimum maintenance policy of a single-unit system to each of the components (subsystems) may not lead to a global optimal maintenance policy for the system as a whole. Our model presented in [19] could be particularly emphasized because it was used as a basis for research in this study. A two-subsystem model is used where each subsystem, as a part of some complex system, was not considered as a single unit. The model includes random failures and those occurring as a consequence of degradation (aging). A serious limitation of this model was the use of only one optimization criterion , i.e. the maximum of complete system availability.

One of the goals of this paper is to develop an availability-cost model for a two component system based on our previous research [20, 10, 11, 19]. Thus the limitations of the single-component system analysis and of considering only one optimization criterion are eliminated. The optimal values of the mean time to preventive maintenance are simultaneously determined by maximizing the availability of the complete system and by minimizing total costs.

These two criteria are conflicting with each other, and the optimization of a solution with respect to a single objective can result in unacceptable results with respect to some other objective. In literature, there exist many algorithms for multi-objective optimization problems (MOPs), and metaheuristic methods are particularly suitable for such a kind of problems. In many practical cases, the application of classical optimization methods for MOPs might be prohibitively expensive in terms of computational time and might also yield a local optimum without recognition that a further search is needed to obtain the global optimum. Hence, the complexity, multimodality and nonlinearity of real, practical problems gave impetus to the development of new, metaheuristic methods that are supposed to yield a “good enough” solution. It should be emphasized that in metaheuristic methods there is no guarantee that optimal solutions will be determined [30]. The general idea is the development of algorithms that can efficiently cope with MOPs and that would generate good quality solutions. In most cases, it is to be expected that the obtained solution will be a near-optimal one, which depends on the nature of the problem, parameters of the applied method, etc. Three well-known and frequently used metaheuristic methods are the real coded genetic algorithm (RCGA), the improved harmony search algorithm (IHSA), and simulated annealing (SA). The popularity of these methods has been reflected in their application in many real life engineering problems and several published studies in the area of maintenance optimization can be found in literature [13, 27, 24]. However, there have been no studies providing comparisons between these three metaheuristic methods in maintenance optimization yet.

The specificity of the previously mentioned maintenance models indicates the need for a careful selection of parameters of algorithms in an optimization process to obtain desired values of output variables (the optimal value of the mean time to preventive maintenance). The overall goal of this paper is to compare the relative performance of the RCGA, IHSA and SA methods to solve real life MOPs. The efficiency of the algorithms is measured with the Taguchi method which is used to specify the proper level of each algorithm parameters [23]. The proposed optimization model uses actual maintenance, failure and costs data for RCVs of a large Serbian public utility company, which are presented and fully discussed in paper [19].

2. Model Description

A general probabilistic maintenance model, which uses state diagrams and the theory of Markov Process, is proposed in [25, 7, 28]. The common concept of these models and the widely accepted fact is that the system (component) failure can be divided into two categories: random failure and failure occurring as a consequence of deterioration (ageing). Here, the Markov model of a multi-state degradation system with two dependent subsystems is considered (see Figure 1.).

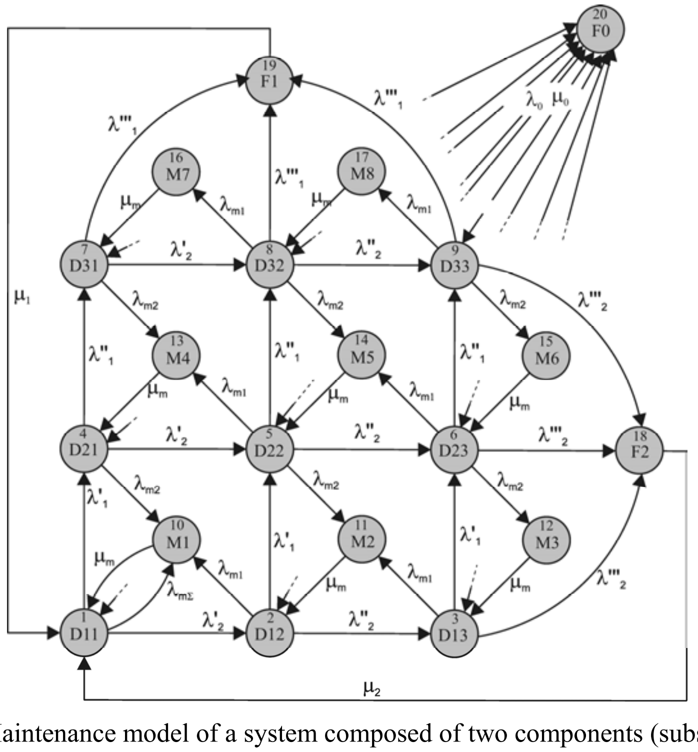

Fig. 1 Maintenance model of a system composed of two components (subsystems)

The proposed model is defined and explained in detail in paper [20] and here only the basic model description and some important assumptions are given. The model includes three stochastic - failure processes (two of them are degradation processes and the third is a random failure process) and a set of maintenance actions and their effects.

It can be assumed that the system degradation process is defined by discrete system states D_{ij} (i = 1, 2, 3 – degradation states of the first subsystem, j = 1, 2, 3 – degradation states of the second subsystem) for which the transition probabilities are equal to the reciprocal values of the mean times spent in corresponding degradation states. These values are $1/\lambda'_1$, $1/\lambda''_1$ and $1/\lambda'''_1$ in the case of subsystem 1 and $1/\lambda'_2$, $1/\lambda''_2$ and $1/\lambda'''_2$ in the case of subsystem 2. If no maintenance is carried out, the system will run through all stages of degradation and will sooner or later reach the failure state (F_1 upon the degradation of subsystem 1, or F_2 upon the degradation of subsystem 2). After the degradation failure, appropriate repair/replace activities bring the system back in the "as good as new" state (state $D_{1,1}$), with the repair and the replace rate μ_1 and μ_2, respectively, for both subsystems. Also, representing the third failure process, the state F_0 denotes the state of the system following random failure (with transition probability λ_0) that can occur at any time but not while maintenance is performed. After the random failure, appropriate repair activities bring the system back in the state from which it has failed with the mean time of repairing the random failure $1/\mu_0$.

Maintenance actions carried out to improve the system condition or to avoid failures can be easily modelled using minimal preventive maintenance states M_k (k = 1÷8). Maintenance is modelled as a Poisson process with the parameters $1/\lambda_{m1}$ and $1/\lambda_{m2}$ that denote mean times to minimal preventive maintenance (for both subsystems) – variables whose optimal values must be determined. After minimal preventive maintenance, the corresponding subsystem is returned to its previous state of degradation, except for the first degradation state D_{11} where the system remains in a state of completion of maintenance actions. The mean duration of minimal preventive maintenance is modelled as $1/\mu_m$.

One of the basic assumptions is that state transitions occur with a constant rate, which means that all transition times are exponentially distributed (the future state of the system is only dependent on the current state). With this assumption, the proposed model can be analyzed by using a Markov process. To date, the continuous-parameter Markov process has been applied most extensively to model reliability and maintenance problems. There are standard methods [1, 19, 20] that can be used to calculate performance measures such as steady-state probabilities P^*_r, (probability that the system is in the state r (r = 1÷20) when $t \rightarrow \infty$, i.e. if "the system works for a long time"), based on which optimization criteria will be defined.

2.1 Optimization of the RCV maintenance process

The optimal values of the mean time to preventive maintenance are determined by maximizing the availability of the complete system with respect to the mean time to minimal preventive maintenance of both subsystems. The multi-objective optimization problem corresponds to the availability and total costs functions that can be expressed, similarly to our findings in [19], as:

$$\max\ A_v(\lambda_m) = \sum_{i=1,\ j=1}^{3} P^*_{D_{i,j}} \quad \min\ C_{TOT}(\lambda_m) =$$
$$C_{PROC} + \sum_{i=1,\ j=1}^{3} (1-d)^{-\max(i,j)} \cdot P^*_{D_{i,j}} \cdot C_{OPER} + \tag{1}$$
$$+ P^*_{F_0} \cdot C_{F_0} + P^*_{F_1} \cdot C_{F_1} + P^*_{F_2} \cdot C_{F_2} + \sum_{k=1}^{8} P^*_{M_k} \cdot C_{PM}$$

within the constraint $1 \leq 1/\lambda_m \leq 315$ (315 working days per year). Here, $P^*_{Di,j}$ represents the steady-state probability of each degradation state, d – the degradation coefficient, P^*_{F0}, P^*_{F1}, P^*_{F2} - the steady-state probabilities (random, degradation1, degradation2, respectively) that the system is in the failure "non-operating" state and P^*_{Mk} – the steady-state probability that the system is in the minimal preventive maintenance state. Also, C_{PROC} – represents procurement costs, C_{OPER} – operational costs in the "as good as new" state, C_{F0}, C_{F1}, C_{F2} – replace/repair costs after random F_0 or degradation failure F_1, F_2, and C_{PM} – costs per preventive maintenance.

Since the optimization model presented by Eq. (1) is a bi-objective optimization problem, the fitness function which represents the problem as a linear combination between single objectives can be defined as [17]:

$$Fit = w_1 \cdot \left(C_{TOT} / C_{TOT\,max}\right) + w_2 \cdot \left(1 - A_v\right) \tag{2}$$

where w_1 and w_2 represent weights which vary between 0 and 1, with the condition $w_1 + w_2 = 1$. The fitness function represents the weighted summation of the normalized total costs function and the unavailability function.

Many engineering optimization problems are very complicated in nature and quite difficult to solve using traditional optimization methods. In recent years, metaheuristic algorithms such as genetic algorithms, simulated annealing, tabu search, particle swarm optimization, ant colony optimization, harmony search and others have been increasingly used by many researchers.

2.1.1 Real coded genetic algorithm and parameters setting

Genetic algorithms, developed by Holland [9], are artificial genetic systems based on the process of natural selection. They are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection and crossover. The evolution of population is performed through a specific number of generations where the next generation gives a better solution than the previous. In the RCGA, the solution is directly represented as a vector of real parameter decision variables; thus the representation of the solutions is very close to the natural formulation of many problems. The use of real parameters makes it possible to use large domains for variables. The RCGAs have been used to solve engineering problems that are complex and difficult to solve by conventional optimization methods as shown in [6, 2].

The implementation of the RCGA requires the determination of six fundamental issues: the chromosome representation, the selection function, the genetic operators, the initialization, the termination and the evaluation function [3]. The first step in the RCGA optimization process is generating an initial population that includes a specific number of chromosomes. Population size is very important for obtaining the best solution. In general, algorithms with smaller populations and smaller number of generations can converge faster as they have less diversity within them, but there is a danger of falling into the local optima area. On the other hand, increasing the population size and the number of generations provides a general optimal solution with high precision but the computational time is very long. The trade-off between computational time, population size and the number of generations needs to be done.

The next important parameter of the RCGA is the selection operator. The selection operator is used to identify a set of parents for the following crossover and mutation operators. Stochastic uniform, proportional (roulette) and tournament selections are the three most common selection schemes. A good literature review of these methods is given in [4].

The new generation is created via crossover and mutation operators which are two other main parameters of the RCGA. Following selection, a crossover operator is applied to randomly chosen parent genotypes and yields one or two offspring genotypes. The operator is applied with a fixed probability (crossover fraction) while the remainder of solutions enter the next generation without being crossed over. This parameter is varied in interval [0.7÷0.82]. In literature there are several crossover operators developed [4] for the RCGA whereby three methods are used most frequently: the scattered, the heuristic and the arithmetic crossover. After selection and crossover, the solutions undergo a process of mutation. The role of mutation in the RCGA is to restore lost or unexpected genetic material into a population to prevent the premature convergence to sub-optimal solutions.

2.1.2 Harmony search algorithm and parameters setting

Harmony search algorithm (HSA), developed by Geem [8], has been successfully applied to various benchmark and real world problems. It is a metaheuristic optimization algorithm conceptualized by using the musical process of searching for a perfect state of harmony. Musical performances seek to find pleasing harmony (a perfect state) as determined by an aesthetic standard, just as the optimization process seeks to find a global solution (a perfect state) as determined by an objective function. The pitch of each musical instrument determines the aesthetic quality, just as the objective function value is determined by the set of values assigned to each decision variable. The optimization procedure of the HSA includes five steps [14].

The algorithm requires several parameters [8], including harmony memory (*HM*), number of improvisations (*NI*), harmony memory considering rate (*HMCR*), pitch adjusting rate (*PAR*), bandwidth vector (*bw*).

The usage of *HM* is important as it is similar to choosing the most fit individuals in the genetic algorithms [30]. In order to increase efficiency of the algorithm it is necessary to select the *HMCR* parameter which takes the value from the interval [0, 1]. If this rate is too low, only few best harmonies are selected and the method may converge too slowly. If this rate is extremely high (near 1), almost all the harmonies are used in the harmony memory, other harmonies are not explored well, which leads to potentially wrong solutions. Therefore, *HMCR* typically takes the value between 0.35 and 0.95.

PAR and *bw* in the HSA are very important parameters in fine-tuning of optimized solution vectors and can be potentially useful in adjusting the convergence rate of the algorithm to the optimal solution. So, fine adjustment of these parameters is needed. If *PAR* is too low, then there is rarely any change. If it is too high, then the algorithm may not converge at all. Thus, usually $0.1 \leq PAR \leq 0.5$ is used. Parameter *bw* is an arbitrary distance bandwidth, that increases the diversity of the solutions.

The traditional HSA uses a fixed value for both *PAR* and *bw*. In the HSA method, *PAR* and *bw* values are adjusted in the initialization step (Step 1) and cannot be changed during new generations. The main drawback of this method appears in the number of iterations the algorithm needs to find an optimal solution.

Mahdavi [14] suggested an improvement to the traditional HSA with the key difference in the way of adjusting *PAR* and *bw*. Namely, to improve the performance of the HSA and to eliminate the drawbacks that originate from the fixed values of *PAR* and *bw*, the improvement to the traditional HSA uses variables *PAR* and *bw* in the improvisation step. In this paper, the improved harmony search algorithm (IHSA) was used.

2.1.3 Simulated annealing method and parameters setting

The concept of simulated annealing is taken from nature and it mimics the metals recrystallization in the process of annealing. Annealing refers to slow cooling of metal that produces low energy state crystallization, whereas fast cooling produces poor crystallization. The SA algorithm starts with a random initial design vector (solution) X_i and initial temperature T. A second design point is created at random in the vicinity of the initial point and the difference in the function values ΔE at these two points is calculated [22] as follows:

$$\Delta E = \Delta f = f_{i+1} - f_i \equiv f\left(X_{i+1}\right) - f\left(X_i\right) \tag{3}$$

If the objective function value (Δf) of a new solution is smaller, the new solution is automatically accepted and becomes the current solution from which the search continues. Otherwise the point is accepted with a probability $p=e^{(-\Delta E/k_B T)}$ where k_B is the Boltzmann constant. This completes one iteration of the SA. Due to the probabilistic acceptance of a non-improving solution, the SA can escape from local optima. At a certain temperature T, a predetermined number of new points are tested. The algorithm is terminated when the current value of temperature is small enough or when changes in the function values (Δf) are sufficiently small.

For a successful implementation of the SA algorithm, the parameters such as the cooling rate, initial and final temperatures, rejection and the balanced number of iterations need to be carefully set. According to Yang [31], the choice of the right initial temperature is crucially important. For a given change Δf, if T is too high ($T \rightarrow \infty$), then $p \rightarrow 1$ and almost all changes will be accepted. If T is too low, then any $\Delta f > 0$ will rarely be accepted and thus the diversity of the solution is limited. In order to find a suitable starting temperature T, any available information about the objective function can be used. If the maximum change $max(\Delta f)$ of the objective function is known, initial temperature T for a given probability p is defined as:

$$T \approx -\frac{max(\Delta f)}{ln\, p} \tag{4}$$

If the possible maximum change of the objective function is not known, the heuristic approach can be used. The cooling rate (α) should be chosen from the interval $0 < \alpha < 1$. The cooling process should be slow enough to allow the system to stabilize easily. Cooling rate is almost always heuristic; moderate execution time should be balanced with the simulated annealing dependence on asymptotic behaviour. In practice, $\alpha = 0.7 \sim 0.95$ is commonly used [30].

A large number of iterations at a particular temperature contributes to better results but increases the execution time of the algorithm. A small number of iterations could result in premature convergence and convergence to local optima.

2.2 Taguchi experimental design

The Taguchi technique is a well-known, unique and powerful technique for product/process quality improvement. It has wide application in engineering design [26,15, 16] and can be applied to many aspects such as optimization, experimental design, sensitivity analysis, parameter estimation, model prediction, etc.

The Taguchi experimental design is a more structured and efficient technique that differs from the classical design of experiment, and, in this sense, it is a relatively simple method. The classical design of experiment (DoE) is sometimes too complex, time consuming and not easy to use [18]. A large number of trials have to be carried out when the number of process factors increases. By using highly fractionated factorial designs and other types of factorial designs obtained from orthogonal (balanced) arrays instead of the full factorial design, the Taguchi experimental design allows for an easy set-up of experiments with a minimum number of trials. Fewer trials imply that time and costs are reduced. In a full factorial design with more factors and several levels of each factor, the total number of trials (N) can be obtained by:

$$N = L^k \tag{5}$$

where L is the number of levels and k is the number of design factors.

Traditionally, data from experiments is used to analyze the mean response. However, in the Taguchi experimental design the mean and the variance of the response (experimental result) at each setting of parameters in the orthogonal array are combined into a single performance measure known as the signal-to-noise (S/N) ratio. Depending on the criterion for the quality characteristic to be optimized, different *S/N* ratios can be chosen: smaller-the-better, larger-the-better, and nominal-the-best [21]. For example, the *S/N* ratio for the smaller-the-better criterion is employed when the aim is to make the response as small as possible. This category of the *S/N* ratio is defined as:

$$\eta = S/N = -10\,log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{6}$$

where y_i is the i – th observed value of the response (quality characteristic) and n is the number of observations in a trial.

In the following subsections, firstly, a pattern of generation of test data and an appropriate Taguchi scheme for each algorithm are presented. Then, the Taguchi experimental design is performed. Finally, the analysis of variance (ANOVA) is applied to determine the effective parameters which have significant impact on the robustness of parameters of optimization algorithms.

The Taguchi method is a robust design technique, which in its essence optimizes the settings of the process factor values as close as possible to the target factor values, with minimum variation. An experiment was conducted to test the performance of each algorithm. As mentioned in previous sections, parameters which were considered for each optimization algorithm are as follows:

1. Parameters of RCGA - mutation type, population size, number of generations, reproduction, crossover type, and selection strategy.
2. Parameters of IHSA - number of improvisation, harmony memory size, harmony memory considering rate, pitch adjusting rate (PAR_{min} and PAR_{max}), and bandwidth (bw_{min} and bw_{max}).
3. Parameters of SA - initial temperature, cooling factor, number of rejection for simulation process, and number of iterations.

Each of these factors can have some levels. Table 1 shows levels of the RCGA factors, Table 2 shows levels of the IHSA factors and levels of the SA factors are presented in Table 3.

Table 1 Factor level in RCGA

Factors	Index of level	Levels
Mutation function	1	Uniform
	2	Adaptive feasible
Population size	1	5
	2	10
	3	20
Generations	1	10
	2	25
	3	55
Reproduction (Crossover fraction)	1	0.7
	2	0.75
	3	0.82
Crossover function	1	Scattered
	2	Heuristic
	3	Arithmetic
Selection function	1	Stochastic uniform
	2	Roulette
	3	Tournament

The full factorial design requires 2^1 x 3^5 = 486 experiments for the RCGA, 3^7 = 2187 experiments for the IHSA and 3^4 = 81 experiments for SA. Considering statistical theories, it is not required to experiment all combinations of factors. For this reason, fractional replicated designs were used. To select an appropriate orthogonal array, the number of degrees of freedom should be calculated.

Degree of freedom in the RCGA is calculated as 1 + (2 x 5) + 6 = 17. That is one degree of freedom for the mutation type with two levels, two degrees of freedom for fife factors with three levels and six degrees of freedom for error. Therefore, the appropriate array must contain at least twenty-six rows. The proper orthogonal array is L_{18} (2^1 x 3^5). The number of degrees of freedom in the IHSA is (2 x 7) + 12 = 26.

Table 2 Factor level in IHSA

Factors	Index of level	Levels
Improvisation Number - *IN*	1	100
	2	300
	3	500
Harmony memory - *HM*	1	10
	2	20
	3	40
Harmony memory considering rate - *HMCR*	1	0.35
	2	0.65
	3	0.85
Pitch adjusting rate - PAR_{min}	1	0.1
	2	0.3
	3	0.5
Pitch adjusting rate - PAR_{max}	1	0.8
	2	0.9
	3	0.99
Bandwidth - bw_{min}	1	0.00001
	3	0.001
	3	0.1
Bandwidth - bw_{max}	1	0.2
	2	0.6
	3	1

Table 3 Factor level in SA

Factors	Index of level	Levels
Initial temperature	1	10
	2	100
	3	1000
Cooling factor	1	0.4
	2	0.6
	3	0.95
Rejections	1	5
	2	10
	3	15
Iterations	1	10
	2	20
	3	40

That means two degrees of freedom for seven factors with three levels and twelve degrees of freedom for error. Therefore, an appropriate array must contain at least twenty-six rows. The proper orthogonal array is L_{27} (3^7). The sum of the required degrees of freedom in SA is calculated as (2 x 4) = 8. That is two degrees of freedom for four factors with three levels. Hence, an appropriate array must have at least nine rows. The proper orthogonal array is L_9 (3^4).

3. Results and Discussion

In this section, three different metaheuristic optimization methods, the real coded genetic algorithm, the improved harmony search algorithm and simulated annealing, were experimented based on the model of the observed real life problem of RCV maintenance optimization. Namely, the implementation of the developed model and metaheuristic optimization is applied to the considered problem of a two-component transportation system for waste collection, transport and disposal.

3.1 A transportation system for waste collection, transport and disposal

An effective and efficient maintenance process is crucial for the successful work of public utility companies (PUCs). Many utility companies in Serbia, especially those in smaller towns, have a problem with the diverse structure of their vehicle fleets, as well as with the vehicles that are at the end of their life cycle. This fact points to the need to develop a special methodology based on the statistical monitoring of the state of trucks and determination of optimal values of the mean time to preventive maintenance.

The system for waste collection, transport and disposal, utilized by the PUC Mediana Niš, is considered in this paper. From the aspect of the system functioning, the territory of the city (Niš, Serbia) is divided into two groups of areas: those where waste is collected in bins and those where waste is collected in containers. In a similar way, according to the type of superstructure of the basic vehicles (working devices), RCVs are divided into two groups (subsystem 1 and subsystem 2). For both subsystems the failure and costs data, from the database of the PUC Mediana information system, are shown in Table 4.

Other parameters defined in the maintenance model and the optimization criteria are set as: $d = 0.15$, $w_1 = 0.5$ and $w_2 = 0.5$ (both criteria have equal importance).

Table 4 Parameters of maintenance model and individual costs of RCV for the large PUC "Mediana – Niš", Serbia

Parameters of maintenance model			Individual costs		
Parameter	Subsystem 1 [day^{-1}]	Subsystem 2 [day^{-1}]	Parameter	Subsystem 1 [€/day]	Subsystem 2 [€/day]
λ_0	0.01003	0.01003	C_{PROC}	23.225	22.954
λ'	0.01092	0.01979	C_{OPER}	22.340	22.340
λ''	0.02261	0.03912	C_{F0}	36.784	36.784
λ'''	0.03478	0.05782	C_{F1}	46.784	
μ_0	0.26389	0.26389	C_{F2}		46.784
μ_1	0.08462	0.08462	C_{PM}	31.784	31.784
μ_2	0.10409	0.10409			
μ_m	1	1			

3.2 Numerical results

The main point of interest in this paper is a comparison of different optimization methods used to optimize the availability and total costs of a multi-state degradation system with two dependent subsystems. It has been found that all three optimization methods have relatively fast convergence behaviour for this class of problems, which could also be credited to the carefully developed model and fitness function. In order to compare the optimization methods, in the RCGA and the IHSA twenty-seven and in SA nine different level combinations of control factors were considered. For each trial, 10 replications were performed. Figures 2-4 show the sensitivity of the parameters of the applied algorithms.

To increase robustness of the algorithms, their parameters were carefully set by the described methodology. Appropriate levels for each parameter of the RCGA are: crossover fraction - 0.82; population size - 20; generations - 55; mutation function - adaptive feasible; crossover function - heuristic; selection function - roulette. Appropriate levels for each parameter of the IHSA are: number of improvisation - 500; harmony memory - 20; harmony memory considering rate - 0.65; pitch adjusting rate min - 0.5; pitch adjusting rate max - 0.99; bandwidth min - 0.01; bandwidth max - 0.2. Finally, appropriate levels for the SA parameters are: initial temperature - 100; cooling rate - 0.95; rejections - 10; iterations - 40.

By optimizing expression (1), optimal values of the mean time to minimal preventive maintenance (λ_{m1} and λ_{m2}) for both criteria were determined. When only one criterion (availability) is considered, the minimal preventive maintenance frequency is λ_{m1}^{-1} = 26.870 [day] for subsystem 1 and λ_{m2}^{-1} = 16.374 [day] for subsystem 2 while the maximum value of availability is $A_{v\ max}$ = 0.8779236970. If total costs are the optimization criteria, the optimal values of the mean time to minimal preventive maintenance are λ_{m1}^{-1} = 3.206 [day] and λ_{m2}^{-1} = 5.639 [day], while their corresponding minimal value of the normalized total costs is C_u/C_{max} = 0.8654272804. By optimizing expression (2), i.e when both criteria are considered simultaneously, the results are: λ_{m1}^{-1} = 7.750 [day], λ_{m2}^{-1} = 11.932 [day] and the minimum of the fitness function is *min*(*fit*) = 0.5124016097.

The analysis of variance (ANOVA), which is given in Table 7, is carried out for the statistical significance test of factors. Since there is not an error term, F -statistics cannot be calculated. Hence, ANOVA is carried out again after pooling the factors such as initial temperature in SA.

The results which are presented in Tables 5, 6 and 8 indicate that in the RCGA some factors such as population size, selection function and generation have a significant impact on the robustness of the algorithm. Similarly, in the IHSA, the number of improvisations, the harmony memory size and the harmony memory considering rate, as well as in SA the parameters such as cooling rate and iteration, have a significant effect on the robustness of the algorithms.

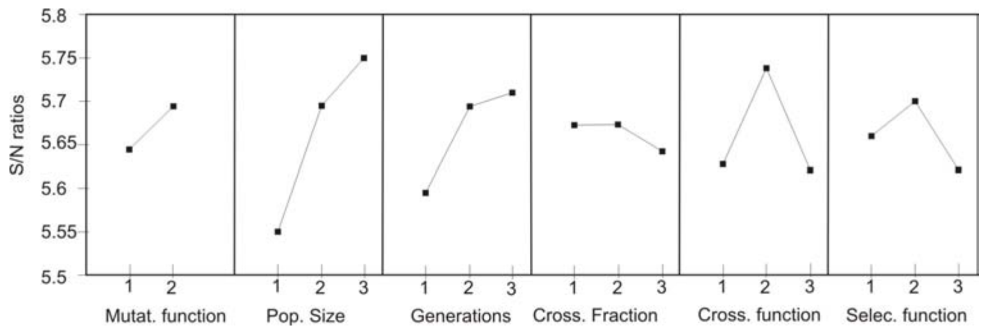

Fig. 2 The average S/N ratio plot at each level for objective values in RCGA

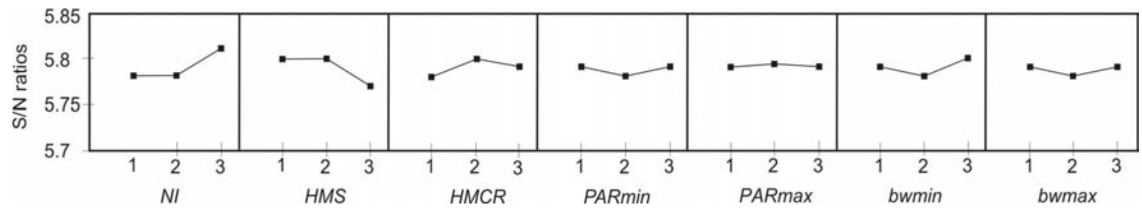

Fig. 3 The average S/N ratio plot at each level for objective values in IHSA

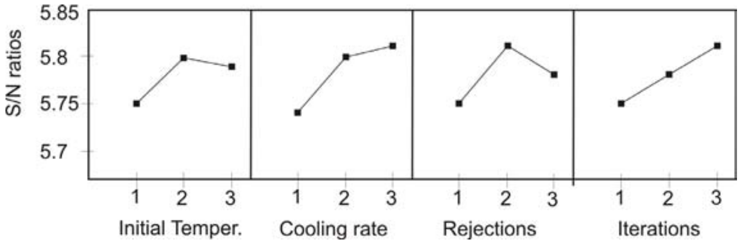

Fig. 4 The average *S/N* ratio plot at each level for objective values in SA

Table 5 ANOVA for S/N ratio within RCGA

Factor	DOF	Sum of squares	Mean square	F (variance ratio)	Percent %
Mutation function	1	0.0138	0.0138	4.3100	4.8215
Population size	2	0.1308	0.0653	20.3921	45.6236
Generations	2	0.0494	0.0247	7.7167	17.2648
Crossover fraction	2	0.0036	0.0018	0.5724	1.2807
Crossover function	2	0.0508	0.0254	7.9326	17.7478
Selection function	2	0.0187	0.0093	2.9273	6.5494
Error	6	0.0192	0.0032		6.7119
Total	17	0.2866			

Table 6 ANOVA for S/N ratio within IHSA

Factor	DOF	Sum of squares	Mean square	F (variance ratio)	Percent %
Number of improvisation	2	0.0048	0.0024	11.2429	25.4775
Harmony memory size	2	0.0057	0.0028	13.4625	30.5072
Harmony memory considering rate	2	0.0034	0.0017	7.9842	18.0930
Pitch adjusting rate max	2	0.0006	0.0003	1.4052	3.1844
Pitch adjusting rate min	2	0.0000	0.0000	0.0680	0.1542
Bandwidth max	2	0.0010	0.0005	2.3570	5.3411
Bandwidth min	2	0.0007	0.0003	1.6089	3.6460
Error	12	0.0025	0.0002		13.5965
Total	26	0.0187			

Table 7 ANOVA for S/N ratio within SA

Factor	DOF	Sum of squares	Mean square	F (variance ratio)	Percent %
Initial temperature	2	0.0039	0.0019	**	15.0434
Cooling rate	2	0.0087	0.0044	**	33.7288
Rejections	2	0.0050	0.0025	**	19.1878
Iterations	2	0.0050	0.0025	**	19.1878
Error	0	0.0033	0.0000		0.0000
Total	8	0.0259			

Table 8 ANOVA for S/N ratio within SA

Factor	DOF	Sum of squares	Mean square	F (variance ratio)	Percent %
Cooling rate	2	0.0087	0.0044	1.2091	33.7288
Rejections	2	0.0050	0.0025	0.6878	19.1878
Iterations	2	0.0050	0.0025	0.6878	19.1878
Error	2	0.0072	0.0036		27.8956
Total	8	0.0259			

4. Conclusion

In this paper, a comparative analysis of metaheuristic maintenance optimizations of refuse collection vehicles is presented using the Taguchi experimental design. A probabilistic maintenance model for the optimization of availability and total costs of a multi-state degradation system with two dependent subsystems was used. The results obtained by using different metaheuristic optimization methods, namely the RCGA, the IHSA and SA, are compared. In order to investigate the performance of these three algorithms for the considered problem, the Taguchi parameter design method for tuning the parameters of each algorithm was applied. In the RCGA, 18 experiments were performed. Using the full factorial design it was concluded that the population size, the selection strategy, the mutation type and the number of generations are the factors that have the greatest influence on the performance of this algorithm among the 6 considered factors. Similarly, for the IHSA, where 27 experiments were done, the number of improvisation, the harmony memory size and the harmony memory considering rate are the factors that have the strongest effect on its performance among the 7 considered factors. For SA, 9 experiments were performed and their results show that among the 4 considered factors, two factors, i.e. the number of iterations and the number of rejections, affect the algorithm performance considerably.

Based on the obtained results, it is clear that for this class of problems all three metaheuristic algorithms generally converge to an optimal solution with relatively small performance sensitivity. Nevertheless, in some cases (for some specific parameters) the algorithms have bad convergence and the authorspropose to use the suggested values of parameters for a similar class of problems.

The presented model is a good representation of the real life system and the obtained optimal values of the mean time to preventive maintenance can be effectively applied to vehicle fleets with the diverse structure and vehicles that are near the end of their life cycle.

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