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MULTI-OBJECTIVE SIMULATION OPTIMIZATION USING GREY-BASED TAGUCHI METHOD WITH FUZZY AHP WEIGHTING

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ABSTRACT

Simulation is a powerful tool for analyzing and designing of industrial and service systems. But simulation can't optimize the system elements and needs additional methods for optimization. In this study a multi-objective simulation optimization is dealt with. To determine the optimum factor levels, grey-based Taguchi approach is used. Since Taguchi method is designed for single objective problems, grey relational analysis is combined with Taguchi method to solve this multi-objective simulation optimization problem. Additionally, in the stage of grade relational calculation of grey relational analysis (GRA) fuzzy AHP weighting process is adopted to determine the weights of grey relational coefficients.
Keywords: Multi-objective simulation optimization, grey-based Taguchi, fuzzy AHP.

BULANIK AHP AĞIRLIKLANDIRMALI GRİ TABANLI TAGUCHI METODU İLE ÇOK AMAÇLI BENZETİM OPTİMİZASYONU

ÖZ

Benzetim, üretim ve hizmet sistemlerinin analizinde sıklıkla kullanılan güçlü bir araçtır. Fakat benzetim ile ele alınan sistemin optimizasyonunu sağlayacak bileşenlerin optimum değerlerinin elde edilmesi mümkün olmadığından, bu amaçla ilave yöntemlere ihtiyaç vardır. Bu çalışmada çok amaçlı bir benzetim optimizasyonu problemi ele alınmaktadır. Faktörlerin optimum düzeylerine karar vermek için gri tabanlı Taguchi yaklaşımı kullanılmıştır. Taguchi metodu tek amaçlı problemler için tasarlanmış bir yöntem olduğundan çok amaçlı benzetim probleminin optimizasyonu için gri ilişkisel analiz bu metotla birleştirilmiştir. Ayrıca, gri ilişkisel derecenin hesaplanması aşamasında gri ilişkisel katsayıların belirlenmesinde bulanık AHP yaklaşımı kullanılmıştır.
Anahtar Sözcükler: Çok amaçlı benzetim optimizasyonu, gri tabanlı Taguchi metodu, bulanık AHP.

1. INTRODUCTION

Simulation is widely used in manufacturing and service systems analysis and design. By simulation, system behavior can be modeled more realistic due to its stochastic nature. Simulation modeling is an effective tool for evaluating different configurations of these complex and/or stochastic systems. Furthermore simulation gives the end user an understanding for the

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consequences and effects of each system design alternative or system configuration without having to experiment on the real system [1].

Simulation models don't provide the optimum configuration of the system parameters. To obtain optimum parameter configuration form a simulation model, all possible solutions need to be fed into the simulation system. This method is very time consuming and costly. Various simulation optimization techniques are used and developed to avoid these disadvantages. A general simulation optimization methodology consists of an optimization module that guides the search direction and a simulation model that evaluates performances of candidate solutions. Simulation optimization methods use one or more discrete event simulation models instead of analytical objective function and constraints as in mathematical programming techniques [2].

There are many approaches to carry out the integration of simulation model and optimization techniques such as response surface methods, gradient search methods, stochastic approximation methods and heuristic search methods [3]. There are applications of these methodologies both for single objective and multi objective simulation optimization problems.

Multi objective simulation optimization problems deal with the simultaneous optimization of the conflicting at least two objectives. In multi objective simulation optimization literature there are many techniques used for these type problems. Lin et. al. [4], combines the genetic algorithm with data envelopment analysis used to evaluate the simulation results and guide the search process in a surgical service to determine resource levels. Zhang [5], presents a combination of particle swarm optimization and rank-selection method for optimizing equipment-configurations of earthmoving operations. Yang et. al. [6], use a dual-response system and scatter-search method for a multi response simulation problem Willis and Jones [7], combine a simulation model, a non-exhaustive heuristic search algorithm with an embedded multi-objective optimization technique, and database technologies on an inventory problem. Syberfeldt et. al. [8], use evolutionary algorithms with artificial neural network for multi-objective simulation optimization to improve a manufacturing cell at Volvo Aero in Sweden. Lee et. al. [9], integrates multi-objective evolutionary algorithm with multi-objective computing budget allocation method for the multi-objective simulation optimization problem. Alrefaei and Diabat [10], presents a simulated annealing algorithm for solving multi-objective simulation optimization problems. Teng et.al. [11], extend the ordinal optimization techniques for multi-objective simulation optimization problems by using the concept of Pareto optimality. Pasandideh and Niaki [12], integrate desirability function and simulation approach with a genetic algorithm. The desirability function is responsible for modeling the multi-response statistical problem, the simulation approach generates required input data from a simulated system, and the genetic algorithm tries to optimize the model. Kuo et.al. [13], proposes a grey-based Taguchi method to solve the multi-response simulation problem. Yang and Chou [14] combines multi attribute decision making method TOPSIS with Taguchi quality/loss function for a multi response simulation optimization problem.

Simulation optimization problems can be designed as a factorial design problem. Discrete values of the decision variables and sampling variability is enough condition. Taguchi method is one of the methods to solve factorial design problems. The initial forms of factorial design methods and Taguchi method are for the single response problems. To solve multi response problems all responses need to be combined into a single value. For this purpose, Taguchi method and the grey relational analysis can be used together and called as grey based Taguchi. In many areas there are many applications of grey based Taguchi including simulation optimization.

In this study we use grey based Taguchi method for simulation optimization but in the stage of grade relational calculation weighting, fuzzy AHP method is adopted to determine the weights of grey relational coefficients. In section 2 grey based Taguchi method with fuzzy AHP weighting is introduced, in section 3 case study is presented and in section 4 conclusions are presented.

2. THE GREY-BASED TAGUCHI METHOD WITH FUZZY AHP WEIGHTING

The Taguchi method separates the factors that can affect the performance of a system as controllable factors and non-controllable factors. The aim of the Taguchi method is to determine the best levels of controllable factor combinations and design products and processes that show the least change possible in case of non-controllable factors [15]. This method is based on orthogonal array of experiments.

Orthogonal arrays and Signal/Noise (S/N) ratios are two main components of the Taguchi method. An orthogonal array is used to reduce testing time/cost. To drastically reduce the number of tests while still gaining significant insight on important factors and optimal settings, Taguchi recommended the use of eighteen basic orthogonal fractional factorial arrays known as the standard orthogonal arrays. On the analysis side, Taguchi advocated the S/N ratio as a single indicator that jointly and simultaneously considers the average value and standard deviation of test results to determine the relative importance of the factors under study. The S/N ratio can be categorized into three types as the smaller the better type, the larger the better type and the nominal the better type. Selection of the appropriate S/N ratio depends on the features of responses [16].

Taguchi method is originally for single response problems. To use for multi response problems, this method needs additional features. For this purpose Taguchi method is coupled with grey relational analysis and called as grey-based Taguchi. Grey relational analysis was introduced in 1982 by Deng and is a part of grey theory. Grey relational analysis solves multi-attribute decision making problems by combing the entire performance attribute into one single value. As a result, the original problem becomes a single decision making problem. This method quantifies the influences of various factors and their relation which is called the whitening of factor relation. Black is represented as lack of information. Thus the information that is either incomplete or undetermined is called grey. The system having incomplete information is called grey system [17].

In the grey relation grade calculation stage of grey relational analysis weights of the grey relational coefficient must be determined. For this stage there is not a clear method of weight determination. In this study, for the determination of the attributes in grey relation grade calculation, fuzzy AHP method is adopted. AHP is a systematic analytical model and an effective decision-making method, which aims selecting the best among alternatives by transforming the linguistic assessments into numerical values. But on the other hand, in this method, the evaluation process of alternatives is mostly subjective and qualitative data cannot be represented precisely due to the fuzzy nature of decision-making. To deal with uncertainty due to vagueness and imprecision, Fuzzy AHP, a fuzzy extension of AHP, was recently developed by adding the mathematics of fuzzy logic to the classical AHP.

In Figure 1 the flow of grey-based Taguchi method with fuzzy AHP is presented. First, fifth, sixth and seventh steps of the flow are traditional Taguchi method. Other ones are related with the grey relational analysis.

Designing orthogonal array matrix and conducting experiments: This step is relevant with Taguchi method. In this stage appropriate orthogonal array is designed. By means of orthogonal arrays the needed number of tests for the experiment is reduced and this means reduction of time and effort. Reduced number of tests still includes factors and settings for the problem. For this purpose Taguchi recommends eighteen basic orthogonal arrays. After designing orthogonal array matrix the relevant responses are obtained from the system.

Grey relational generation: For a multi-response design Taguchi method needs additional approaches. Grey relational analysis is one of these approaches. In grey relational analysis experimental data is normalized in range of 0 to 1. This process is called grey relational generation. There are three types of data normalization in grey relation analysis: larger-the-better, smaller-the-better and closer-to-the-desired-value. In this study smaller the better type data normalization is used as in Equation 1.

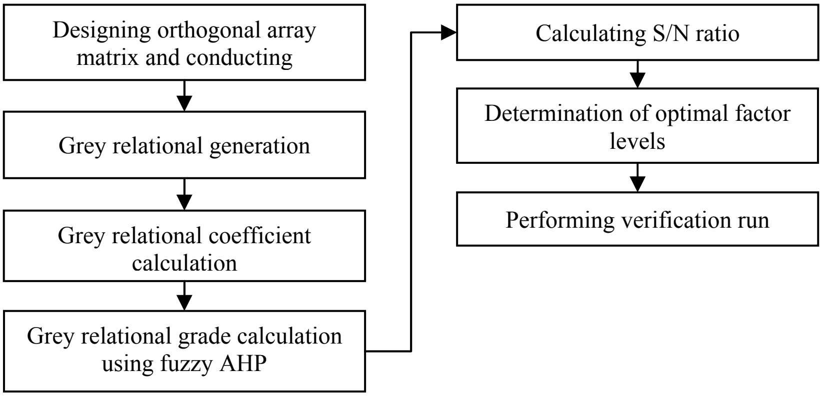

Figure 1. Flow of grey-based Taguchi method with fuzzy AHP

$$x_i=\frac{max(y_i)-y_i}{max(y_i)-min(y_i)} \tag{1}$$

In the equation x_i is the normalized value of the i^{th} alternative, y_i is the response value of the i^{th} alternative, $max\ (y_i)$ is the maximum response and $min\ (y_i)$ is the minimum response value of all alternatives.

Grey relational coefficient calculation: Grey relational coefficient (GRC) expresses relationship between ideal and actual normalized experimental results and is calculated as in Equaiton 2. The larger the coefficient means better result.

$$\varepsilon_i(k)=\frac{\Delta_{min}+\delta\Delta_{max}}{\Delta_{ij}+\delta\Delta_{max}} \tag{2}$$

In this equation, $\varepsilon_i(k)$ means grey relational coefficient of the i^{th} element of the k^{th} response. δ value is identification coefficient and usually set as 0,5. Δ_{min} and Δ_{max} values are largest and smallest values of Δ_{ij} consecutively.

Grey relational grade calculation using fuzzy AHP: The grey relational grade is computed by averaging grey relational coefficient corresponding to each performance characteristic. This coefficient is calculated using Equaiton 3.

$$\tau_i=\sum_{i=1}^{n} w_i\varepsilon_i(k) \tag{3}$$

w_i is the weight of the grey relational coefficients. The value of w_i reflects the judgement of the decision makers' and there is not an exact method of determining the weights. In this study, to determine w_i value the priority weighting process of fuzzy AHP is used. Fuzzy AHP adds the feature of fuzzy logic to classical AHP and it deals with uncertainty due to vagueness and imprecision in classical AHP.

In this study triangular fuzzy numbers are used. A fuzzy number is a convex fuzzy set, characterized by a given interval of real numbers, each with a grade of membership between 0 and 1 and its membership function is piecewise continuous.

The triangular fuzzy number can be represented by $A = (l, m, u)$ where l: lower bound of fuzzy number A, m: the most possible value of A, u: upper bound of fuzzy number A. Here, l and u define the fuzziness of the evaluation data.

The computational technique in this paper is based on the triangular fuzzy numbers, which are defined in Table-1 [18]. These triangular fuzzy numbers are used to represent pairwise comparisons of the decision maker's linguistic assessments in order to capture the vagueness.

Table 1. Fuzzy numbers used for making linguistic assessments

Linguistic scale for importance	Triangular fuzzy scale *(I,m,u)*
Just equal	(1,1,1)
Equally important	(1,1,3)
Weakly important	(1,3,5)
Essential or Strongly important	(3,5,7)
Very strongly important	(5,7,9)
Extremely Preferred	(7,9,9)

"Weights of criteria, w are obtained by using calculation procedure of Chang's Fuzzy AHP method [19]. Obtained values are used in grey relational grade calculation in Equation 3.

Calculating S/N ratio: In Taguchi method, signal to-noise (S/N) is used to represent a response or quality characteristic. The largest S/N ratio means better performance for the combinatorial parameters. There are three types of S/N ratio definition in Taguchi method: the smaller the better type, the larger the better type and the nominal the better type. In this study the larger the better type S/N ratio is used and the S/N ratios are obtained by grey relational grade values.

$$S/N = -10/\log_{10}\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2} \quad (4)$$

Determination of optimal factor levels: In Taguchi method optimum factor levels are determined after obtaining the S/N ratios. In this step main effect plots are useful for determining the optimal levels.

Performing verification run: To obtain the response of factor levels on the performance measure a simulation run is done with the optimum factor levels.

3. CASE STUDY

In this study the corresponding production system manufactures water, electric and natural gas meters. These products are manufactured in three different lines. In every line there are control points. If the operator in the production line encounters any problem the meter is sent to repairing station. If the problem is solved then the meter continues in the production line from the point last sent. In the repairing station the meter may be accepted as scrap with a certain percentage. Completed meters are packaged in the same packaging station.

In Figure 2 main structure of the production line is presented. At the current situation there are total 35 workers in all production system. The performance measures for the production line are workforce productivity and total time in system. Current values for these performance measures are 8,46 and 19,61 consecutively. These results were obtained by running simulation model on ARENA 9.0. As seen, management deals with more than one measure and aims to increase workforce productivity and to decrease total time in system. For this purpose discrete event simulation modeling was used to evaluate the alternatives. Instead of evaluating all alternatives Taguchi design was used with grey relational analysis. In grey relation calculation stage of the algorithm, fuzzy AHP weighting was used to determine the weights of the performance measures using expert opinion from the company.

In this section of the paper, results of multi objective simulation optimization using grey-based Taguchi method with fuzzy AHP weighting approach is presented. Firstly a simulation model of the meter production line was developed using ARENA 9.0. After validating the model, input factors to be optimized and their levels were decided. In this stage the observations and simulation model results were utilized. In Table 2 the input factors and factor levels are given. Totally 4 factors were determined and 3 levels for each factors.

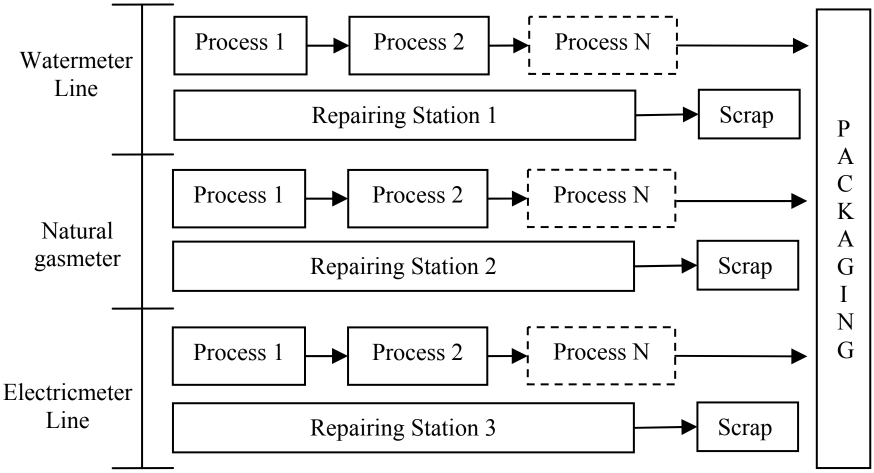

Figure 2. Main structure of the production line

Table 2. Factor levels

Factors	Lower Bound	Middle Bound	Upper Bound
No. of workers in repairing station 1 (A)	1	2	3
No. of workers in repairing station 2 (B)	1	2	3
No. of workers in repairing station 3 (C)	1	2	3
No. of workers in packaging station (D)	2	3	4

After determining the factors and their levels orthogonal array matrix must be decided and experiments must be conducted. For a problem with three levels and four factors there are totally 3^4=81 experiments but by means of Taguchi orthogonal design this number decreased 9. In other words L_9 design was used for the experiments. In the experiment, output for two type of responses were recorded: Workforce productivity (WP) and time in system (TIS). In Table 3 the results for experiment are shown.

Table 3. Results of experiment

No	**Factor Combinations**	**Mean Values**	
		WP	**TIS**
1	$A_1B_1C_1D_1$	8,455	18,404
2	$A_1B_2C_2D_2$	10,540	17,716
3	$A_1B_3C_3D_3$	10,313	19,608
4	$A_2B_1C_2D_3$	11,831	18,060
5	$A_2B_2C_3D_1$	11,047	14,104
6	$A_2B_3C_1D_2$	11,023	18,576
7	$A_3B_1C_3D_3$	10,806	16,288
8	$A_3B_2C_1D_3$	12,209	15,016
9	$A_3B_3C_2D_1$	12,209	17,554

Workforce productivity larger the better type and time in system smaller the better type responses. Since this problem is multi objective, after calculating responses grey relational generation must be conducted. For workforce productivity and time in system grey relational generation is calculated by Equation 1. The grey relational generation for each performance measure is calculated separately and showed in Table 4.

Table 4. Results of grey relational generation

	WP	TIS
X_0	1,00	1,00
1	0,000	0,219
2	0,555	0,344
3	0,495	0,000
4	0,899	0,281
5	0,690	1,000
6	0,684	0,188
7	0,626	0,603
8	1,000	0,834
9	1,000	0,373

After calculating grey relational generation the next step is grey relational coefficient calculation. In this step Equation 2 is used and the identification coefficient δ set as 0,5. The results are given in Table 5.

Table 5. Results of grey relational coefficients

	WP	TIS
1	1,000	0,696
2	0,474	0,593
3	0,503	1,000
4	0,357	0,640
5	0,420	0,333
6	0,422	0,727
7	0,444	0,453
8	0,333	0,375
9	0,333	0,573

Grey relational grade calculation is next step. In this stage we used fuzzy AHP method for determining the weights of each performance measure. The pairwise comparison matrix is showed in Table 6.

Table 6. Pairwise comparison matrix of performance measures

	WP	TIS
WP	(1,1,1)	(1,3,5)
TIS	(1/5,1/3,1)	(1,1,1)

Using fuzzy AHP methodology the weights of the performance measures were calculated as 0.351 and 0.649. In Equation 3 the w value were set as these values. Grey relational grade calculation results are given in Table 7.

In Table 7 best performance is given by the third experiment since it has the largest grey relational grade value. These results were used for optimal factor level determination. Grey relational grade values were used as responses of experimental design of Taguchi method. In

Table 8, larger the better S/N ratios of Taguchi design, calculated by using Equation 4, are presented.

Table 7. Grey relation grade calculation results

No	Grey relational grade
1	0,802
2	0,551
3	0,825
4	0,541
5	0,364
6	0,620
7	0,450
8	0,360
9	0,489

Table 8. S/N ratios of Taguchi design with grey relational grade values as response

No	Factor Combinations	Grey relational grade	S/N Ratio
1	$A_1B_1C_1D_1$	0,802	-1,917
2	$A_1B_2C_2D_2$	0,551	-5,177
3	$A_1B_3C_3D_3$	0,825	-1,671
4	$A_2B_1C_2D_3$	0,541	-5,336
5	$A_2B_2C_3D_1$	0,364	-8,778
6	$A_2B_3C_1D_2$	0,620	-4,152
7	$A_3B_1C_3D_3$	0,450	-6,936
8	$A_3B_2C_1D_3$	0,360	-8,874
9	$A_3B_3C_2D_1$	0,489	-6,214

To decide the optimum factor level combination we need to estimate the effect of each factor at each level. For example, estimation of effect of factor A at level 1 (η_{A1}) is calculated as in Equation 5 using grey relational grades in Table 8.

$$\begin{aligned}\eta_{A1} &= (\tau_1 + \tau_2 + \tau_3)/3 \\ &= (0{,}802 + 0{,}551 + 0{,}825)/3 = 0{,}7260\end{aligned} \tag{5}$$

Furthermore average grey relational grade by S/N ratios can be calculated in the same way with the factor levels. In Table 9 average grey relational grade by all factor levels and in Figure 3 main effect plots for S/N ratios are presented. Values in effect plots are obtained as factor levels using S/N ratios in Table 8. Results in Table 9 and Figure 3 give the information of best factor level combination.

In Table 9 the bold values say the best level for each factor. According to this best factor levels combination is $A_1B_3C_1D_3$. Also in Figure 3 we can see each factor level giving the maximum objective value. The best factor level combination is $A_1B_3C_1D_3$ again according to Figure 3. This means number of workers in repairing station 1 (A) is 1, number of workers in repairing station 2 (B) is 3, number of workers in repairing station 3 (C) is 1 and number of workers in packaging station (D) is 4.

Table 9. Average grey relational grade by factor levels

Level	A	B	C	D
1	**0,7260**	0,5977	**0,5940**	0,5517
2	0,5083	0,4250	0,5270	0,5403
3	0,4330	**0,6447**	0,5463	**0,5753**

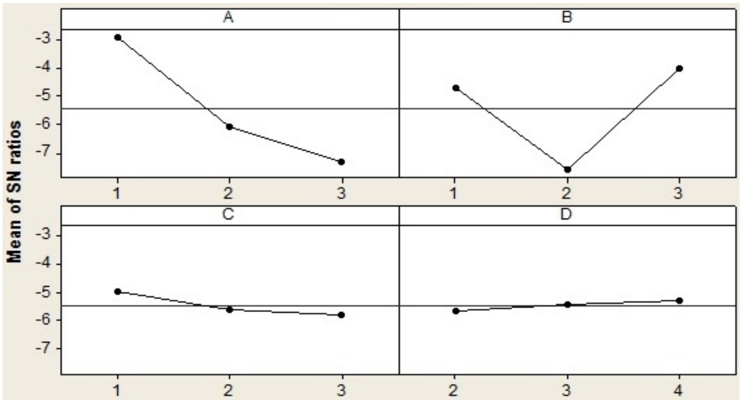

Figure 3. Main effect plots for S/N ratios

Using found optimal factor levels simulation model was run. In this run workforce productivity is 10,72 and time in system is 16,18. At the current situation of the system workforce productivity is 8,46 and time in system is 18,40. In the new system while there is increase in work force productivity by 27% and decrease in time in system value by 12%.

4. CONCLUSIONS

In this study, the grey-based Taguchi method with fuzzy AHP weighting was proposed to solve a multi-response simulation optimization problem. Combining the procedure of the Taguchi method and grey relational analysis with fuzzy AHP weighting a multi-response problem transformed to a single-response problem. The results of the study showed that the grey relational analysis procedure is simple and straightforward in calculations and optimization and it is very suitable for solving multi-response simulation optimization problems. Furthermore, the methodology can be used for problems have more than one response.

In this study conflicting two objectives were tried to be optimized: workforce productivity and time in system. Using proposed methodology in the study number of workers in repairing station 1 (A), number of workers in repairing station 2 (B), number of workers in repairing station 3 (C) and number of workers in packaging station (D) were tried to be optimized. The number of workers in each station is 1,1,1 and 2. At the current situation of the system, workforce productivity is 8,46 and time in system is 18,40. Applying grey-based Taguchi method with fuzzy AHP weighting methodology optimized values of the factors were found as 1,3,1 and 4. In new situation, in work force productivity is 10,72 (increase by 27%) and time in system is 16,18 (decrease by 12%).

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