Novel Approach to Multi-Response Optimisation for Correlated Responses

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This paper presents a novel, general and intelligent approach to multi-response process optimisation, whose purpose is to obtain a single optimum setting of process parameters that meets specifications of all considered, possibly correlated, responses. The approach is based on Taguchi quality loss function, multivariate statistical methods: Principal componenet analysis and Grey relational analysis, and artificial intelligence techniques: Artificial neural networks and Genehic algorithm.

The proposed model considers process optimisation in a general case where analytical relations and interdependences in a process are unknown, thus making it applicable to various types of process optimisation problems.

The implementation of the suggested approach is presented on a study that discusses the optimisation of thermosonic gold wire bonding process in semiconductor industry, for the assembly of microelectronic devices. The results confirm the effectiveness of this approach in the presence of three correlated responses (product quality characteristics).

Keywords: *Taguchi method, quality improvement, multi-response optimisation, quality loss function, principal component analysis, grey relational analysis, artificial neural network, genetic algorithm.*

1. INTRODUCTION

Taguchi's robust parameter design has been proven effective in solving many process optimisation problems in single-response systems. The Taguchi method combines experimental design with quality loss issue that is caused by deviation of product quality characteristic from the target value specified by the customer. Unlike other experimental design methods, Taguchi's technique allows us to study the variation of process and ultimately to optimise the process variability as well as target, using Signal-to-Noise (SN) ratio, which presents the ratio between response mean (control factors effect) and variation (noise factors effect). The Taguchi method in itself optimises a single response or quality characteristic, providing the optimal set of process parameters. This particular setting, however, may not provide the desired results for other quality characteristics of a product/process. In such cases, a single optimum setting of process parameters needs to be identified, so that the specifications of all quality characteristics are met. The complexity of the problem increases when the considered quality characteristics are correlated.

However, several characteristics of a product are usually considered for product quality by the customer. Hence, multi-response optimisation has become an increasingly important issue in a modern manufacturing practice, particularly in situations where more than one correlated responses must be assessed simultaneously.

Several recent studies were centred on solving the multi-response optimisation problem.

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The most commonly used method for multi-response optimisation is Response Surface Methodology (RSM), proven to be effective in many applications. However, there are certain limitations regarding RSM application for multi-response optimisation [1,2]: the RSM does not enable simultaneous optimisation of both mean and variance of the responses; an RSM model may not find the overall (global) best solution and might be trapped easily in a local minimum, when a process is influenced by a large number of variables and is highly non-linear with multiple outputs. Pignatiello's regressional approach [3] that employs a multivariate quality loss function was also subjected to certain concerns [4]: the proposed procedure does not necessarily lead to the global optimum; the possible correlations among the responses may still not be considered; a factor that is significant in a single-response case may not be significant when considered in a multi-response case.

To date, the Taguchi method has not proved to be functional for optimising the multi-response problem; the sole path was relying on engineers' judgement or in combination with RMS [5,6]. There are various methods for multi-response optimisation based on Taguchi static robust design, actually on the transformation of Taguchi's quality loss function [1,4] or SN ratio [7] for multi-response case that employ principal component analysis (PCA) to uncorrelate responses. However, the mentioned approaches in PCA considers only components which variance (eigenvalue) is greater than or equal to one, capturing the larger portion of variance but not the total variance of responses. Wang and Tong [8] used PCA and grey relational analysis (GRA) to transform quality losses for several responses into a single measure, and Wu [9] proposed an approach based on the proportion of quality losses with respect to the known starting conditions. Liao [10] used weighted PCA on SN data. Tong [2] proposed method that combines

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and PCA techniques.

The soft-computing methods for multi-response process optimisation are mainly based on the application of artificial neural networks (ANNs) (i.e. [11]). The approaches based on desirability function analysis (DFA) and ANN ([12]) combines the advantages of both techniques, but it was commented that the methods based on DFA do not always provide the global optimal solution [13]. Hsu [14] combined ANN and PCA to uncorrelate the process model, but only components with eigenvalue greater or equal to one were considered.

Beside the specific shortcomings of the above methods, general limitation of all mentioned approaches is that they consider only discrete parameter values used in the experiment, hence only parameter levels used in the experimental trials could be selected for the optimal parameters setting. In addition, the above methods could not solve multi-response problems where optimisation requires the implementation of knowledge of experts into the formulae. Detailed discussion regarding the above and other related approaches for multi-response optimisation could be found in reference [15].

The GA-based approaches to multi-response problems found in literature are designed to solve one particular problem; hence they are not suitable for general application. Noorossana's approach [13], based on DFA, ANN and GA includes the shortcomings of DFA. Roy and Mehnen [16] used DFA in Pareto front genetic optimisation, assuming that analytical model of the process is known. Khoo and Chen [17] and Drain [18] proposed methods that combine RSM and GA (shortcomings of RSM were commented above). Lau [19] used GA for the optimisation of moulding operations. Mok [20] presented an intelligent system based on case-based reasoning, TOPSIS, ANN and GA, to optimise injection moulding process. Jeong [21] employed GA for shadow mask manufacturing. Hou's method [22] based on RSM, ANN and GA presents an integrated system for wire bonding process optimisation. Tong's approach [23] is based on case-based reasoning, ANN and GA, designed to optimise transfer moulding of electronic packages.

The proposed generic and intelligent approach attempts to overcome the deficiencies of the above methods for multi-response optimisation, owing to the novel multi-criterion methodology that employs [24]:

- Taguchi's quality loss function that adequately represents relative financial significance of responses, and simultaneously assesses the response mean and variation;
- multivariate statistical methods PCA and GRA to uncorrelate and synthesise responses with respect to the customer specifications, which ensures that the weights of responses in a synthetic multi-response performance measure are based on the total variance of the original responses, resulting in improved objectivity of the experimental analysis;
- artificial intelligence techniques to provide correct process modelling (ANN) and ensure global optimal solution (GA) in term of optimal process parameters setting that meets specifications for all responses.

2. INTELLIGENT MULTI-REPONSE PROCESS OPTIMISATION FOR CORRELATED REPONSES

The proposed approach to multi-response process optimisation for correlated responses is based on Taguchi static robust design, multivariate statistical methods and artificial intelligence techniques [24].

2.1 Taguchi method

Taguchi's robust design is a simple, systematic and efficient method to determine optimum settings of control factors, that has been widely used to analyze and optimise a single performance characteristic of a various manufacturing processes. However, the original Taguchi method was not designed to optimise processes with multiple quality characteristics.

The suggested approach is based on Taguchi's quality loss function, because it provides a right metric for multi-criteria decision making. Quality loss function directly represents a financial measure of the customer dissatisfaction with a product's performance as it deviates from a target value. Unlike the conventional weighting methods, the quality loss function is a direct way to indicate the decision maker's preference and is simple to apply. Quality loss function is based on SN ratio which assesses simultaneously the mean value of the quality characteristic and its variation. Since complexity of this issue grows with the growth of the number of responses, this feature is especially important in case of multiple-response optimisation [15].

In the proposed approach for multi-response optimisation for correlated responses, Taguchi's robust design was not applied directly, as not every response may have the same measurement unit and may not be of the same category in the SN ratio analysis.

Taguchi defined the SN ratios [25]:

$$\eta=\left\{\begin{array}{l} -10\log(\frac{1}{n}\sum_{i=1}^{n}y_i^2)......................for.STB \\ 10\log(\frac{\bar{y}^2}{s^2}-\frac{1}{n})\approx 10\log(\frac{\bar{y}^2}{s^2})...for.NTB \\ -10\log(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}).....................for.LTB \end{array}\right\}. \quad (1)$$

The average quality loss is $QL = K \cdot MSD$, where QL is the existing average loss per unit, K is the coefficient, and MSD is the sample mean square deviation when n units of a product are measured [25]:

$$MSD=\left\{\begin{array}{l} \frac{1}{n}\sum_{i=1}^{n}y_i^2..for.STB \\ \frac{1}{n}\sum_{i=1}^{n}(y_i-m)^2=\frac{n-1}{n}.s^2+(\bar{y}-m)^2...for.NTB \\ \frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}..for.LTB \end{array}\right\}, \quad (2)$$

where y is measurable statistic of response; STB, NTB, LTB is smaller-the-better, nominal-the-best, larger-the-better response, respectively; $\overline{y}$ is the sample mean and s^2 is the sample variance of n units.

Quality loss (QL) of the i-th quality characteristic in the k-th trial is:

$$QL_{ik} = K \cdot MSD'_{ik} = 10^{-\frac{\eta'_{ik}}{10}}\ ;\ i = 1, ..., \text{p};\ k = 1, ..., \text{m}. \quad (3)$$

The quality loss of the i-th quality characteristic in the k-th trial QL_{ik} transforms into normalised value $NQL_i(k)$ ($NQL_i(k) \in [0;1]$) by the following formula:

$$NQL_i(k) = \frac{QL_{ik} - \underbrace{\min}_{i} QL_{ik}}{\underbrace{\max}_{i} QL_{ik} - \underbrace{\min}_{i} QL_{ik}};\ i = 1, ..., \text{p};\ k = 1, ..., \text{m}. \quad (4)$$

2.2 Multivariate statistical methods

Principal component analysis (PCA) is considered as an effective means of determining a small number of uncorrelated linear combinations which account for most of the variance in the original number of responses. All principal components are uncorrelated with each other. The sum of variances of the principal components (eigenvalues) is equal to the sum of variances of the original responses.

Since the proposed approach considers general case where correlations among responses exist, PCA is performed on NQL data resulting in a set of uncorrelated components. In contrast to usual practice [1,4,7] where only components with eigenvalue greater than or equal to one are considered, here, in order to capture the total variance of the original data, principal component scores include all principal components. The number of principal components and the number of components of eigenvector correspond to the number of responses. If component of eigenvector of the first principal component PC_1 is denoted as I_{1i}, (i = 1, …, p), the multi-response performance statistics corresponding to PC_1 for NQL can be expressed as:

$$Y_1(k) = \sum_{i=1}^{\text{p}} I_{1i} \cdot NQL_{ik};\ i = 1, ..., \text{p};\ k = 1, ..., \text{m}. \quad (5)$$

The larger the $Y_i(k)$ value, the better the performance of the product/process.

Grey relational analysis (GRA) provides an effective means of dealing with one event that involves multiple decisions and deals with poor, incomplete and uncertain data. GRA can be employed to explain the complicated interrelationship among the data when the trends of their development are either homogeneous or heterogeneous.

Here, GRA is performed on transformed principal scores, resulting in a single multi-response performance measure that adequately takes into account all, possibly correlated, response values with respect to the customer specifications. The weights used in the presented method for determining synthetic multi-response performance measure are based on the total variance of the original responses (from PCA), which results in improved objectivity of the experimental analysis.

GRA is performed on the absolute value of principal component scores $Y_i(k)$. Linear data preprocessing method is employed to transform the principal component scores $|Y_i(k)|$ into a set of standardised multi-response performance statistics $Z_i(k)$:

$$Z_i(k) = \frac{\underbrace{\max}_{i}|Y_i(k)| - |Y_i(k)|}{\underbrace{\max}_{i}|Y_i(k)| - \underbrace{\min}_{i}|Y_i(k)|};\ i = 1, ..., \text{p};\ k = 1, ..., \text{m}. \quad (6)$$

where $\underbrace{\max}_{i}|Y_i(k)|$ ($\underbrace{\min}_{i}|Y_i(k)|$) is the maximum (minimum) value of $|Y_i(k)|$ for the i-th response.

The grey relational coefficient $\xi_i(k)$ is:

$$\xi_i(k) = \frac{\underbrace{\min}_{i}\underbrace{\min}_{k}|Z_i(k) - Z_0(i)| + \varsigma \underbrace{\max}_{i}\underbrace{\max}_{k}|Z_i(k) - Z_0(i)|}{|Z_i(k) - Z_0(i)| + \varsigma \underbrace{\max}_{i}\underbrace{\max}_{k}|Z_i(k) - Z_0(i)|}. \quad (7)$$

where $Z_0(i)$ are ideal sequences with value of 1, and ς is called the distinguishing coefficient ($\varsigma \in [0;1]$).

The grey relational grade γ_k is calculated by a weighted mean, where the weights are determined by percentage of variance of the response $NQLs$ in PCA:

$$\gamma_k = \sum_{i=1}^{\text{p}} \omega_i \xi_i(k), \quad (8)$$

where ω_i is the weight or the percentage of variance of the i-th component in the PCA ($\sum_{i=1}^{\text{p}} \omega_i = 1$).

In the proposed approach, the grey relational grade γ_k is adopted as synthetic performance measure for multi-response process. Knowing the synthetic measure values and factor (process parameter) values for all experimental trials (k = 1, …, m), it is possible to calculate the effects of factors on the synthetic performance measure for all factor levels used in the experiment. The optimal factor (parameter) conditions can be obtained by selecting the maximum of factor effects on multi-response performance measure γ_k. Hereafter, the above presented procedure is referred as the factor effects approach [15,24].

The shortcoming of the presented factor effects approach is that it considers only those discrete values (levels) of factors that are used in experimental trials; hence the optimal factors solution obtained by the factor effects is limited to factor levels used in experiment.

2.3 Artificial intelligence techniques

Artificial neural network (ANN) is powerful technique to generate complex multi-response process models without referring to a particular mathematical model, proven effective in various applications (i.e. [11,13,14]). By applying ANN to learn and model the relations between process parameters and responses, process is considered a "black-box". This feature essentially contributes to generality of the proposed approach, because the model does not depend on the type of relations between responses and process parameters or their correlations, thus making it applicable to different processes. This is particularly important in case when process interrelations are completely or partly unknown.

In this approach, multilayer feed forward ANNs were developed to model the relationship between process parameters and the synthetic multi-response performance measure (γ_k), presenting an input (objective function) for genetic algorithm (GA).

The number of neurons in the input layer of ANNs corresponds to the number of process parameters; the output layer has only one neuron (γ_k). The neurones in the hidden layer are computational units that perform non-linear mapping between inputs and outputs. The training, testing and verification data for ANNs were obtained from experimental results. Input data set contains process parameter values for all experimental trials; output set accommodates synthetic multi-response performance measure γ_k (k = 1, …, m). The process of adjusting the connection weights by repeatedly exposing the network to known input-output data is called training. The error back-propagation (BP) learning method, improved by Levenberg-Marquardt algorithm, was adopted in this approach. The transfer functions for all hidden neurones are tangent sigmoid functions, and for the output neurones are linear functions. It was proven that such choice of transfer functions makes ANN capable to perform successful approximation of various complex functions (i.e. [23]). BP learning employs a gradient descent algorithm to minimise the mean square error (*MSE*) between the target data (original input-output data set) and the predictions of ANN. During the training process, learning rate controls the amount by which weights are changed and momentum avoids a major disruption of the direction of learning in presence of outliers in the training set. A smaller learning rate and larger momentum reduce likelihood that the network will find weights that are a local, but not global minimum [14]. Thus, the adopted values for network training parameters, in this model, are: learning rate $\eta = 0.01$ and momentum factor $\alpha = 0.9$ [24]. Determining the number of hidden neurones is critical in the design of ANN. Since the process modelling is the most sensitive part of the proposed model, various ANNs with different topology (number of hidden neurons) were developed in Matlab, until *MSE* of 10^{-3} is achieved. The best ANN was chosen according to the minimum *MSE* (mean square error between the original (target) data and actual network output (predictions)) criterion. In addition, the coefficient of the correlation between original data and actual network output (*R* value) is considered, with the acceptance level of 0.9 [24].

In the presented approach for multi-response problems, GA was chosen for optimisation due to the following reasons: GA is proven as a potent multiple-directional heuristic search method for optimising highly nonlinear, nonconvex and complex functions; it is less likely to get trapped at a local optimum than traditional gradient-based search methods [16,26].

The trained neural model presents an objective (fitness) function for GA, which, by maximising the objective function finds the optimal parameters setting among all possible solutions in continual multi-dimensional space. In order to obtain optimal performance of GA, large number of GA's parameters must be tuned. According to results of previous analysis [26], the choice of the basic GA's operations (selection and crossover functions) depends on the application. In GA-based approaches discussed in the introduction, only one GA was developed for the observed problems [13,16,19,21,22] and the choice of selection and crossover function were not explained. In order to accept the specifics of each particular problem and to enhance the generality of the proposed model, in this study nine GAs are developed in Matlab, combining the most commonly used types of selection function and crossover function [24].

As explained in the Section 2, the parameter settings obtained by the factor effects approach is the optimal set found in the space of discrete solution (parameter levels used in the experiment). Since this set presents potentially good solution, it serves as a basis to form initial population in GAs. This feature of the suggested model is of essential importance, because it allows GAs to converge to the global optimum faster and enhance its capability to find the actual global solution in the given number of generations [24].

In order to ensure the optimal performance of GA, the rest of operating parameters were: chromosomes are presented in natural presentation; population size is equal or larger than five times dimensionality (number of process parameters); scaling function is "rank"; reproduction parameters are: elite count = 2, crossover fraction = 0.9; mutation function is "adaptive feasible".

The nine GAs were run for 2000 repetitions (generations). The best GA is chosen according to the best fitness value (on-line performance criteria), which is presented by the synthetic multi-response performance measure. The most desirable solution with the highest fitness function value (synthetic multi-response performance measure γ_k) presents the final solution. Additional criterion is the best off-line performance criteria (the mean of the best fitness values through the whole run). Finally, the solution of the best GA was adopted as the final optimal parameters setting in continuous multi-dimensional space [24].

GA considers all continual parameter values between corresponding bounds, in contrast to traditional experimentation methods that consider only those (discrete) values that have been used in the experimental trials. Relaying on this and setting the GA's parameters properly (as described above), the proposed approach ensures optimal performance of GA to converge to the global rather than local optimal solution of multi-response optimisation problem [24].

3. IMPLEMENTATION

3.1 Problem description

The goal of the presented study was to establish the process parameters window for several machines, for the part of thermosonic gold wire bonding process which refers to forming the bonds between gold wire and aluminium die pads in microelectronic devices assembly.

Thermosonic wire bonding is the most widely used assembly technique in the semiconductor industry to interconnect the internal circuitry (IC) of the die to the external world. This method uses bond force, bond power, time, temperature and ultrasonic energy to form the ball bonds at the die pads (above the IC) and welds at the output leads. Typically for the ball bond, the metallurgical interface is between gold wire and aluminium bond pad.

During engineering analysis, it has been noticed that performing the wire bonding process with the same set of parameter values on different machines (of the same type) gives different results for product quality characteristics (responses). Precisely, Machine 1 is adopted as referential machine, the representative of a whole group of machines who show the same behaviour (give the same response values for the given parameter settings). The Machine 2 is the one whose behaviour significantly deviates from the rest of the group of machines. In order to overcome this deficiency, it was decided to establish a process parameters window for two basic process parameters, to ensure that products produced on all machines in the whole group will meet customer specifications for the specified product quality characteristics. From this reason, the experiment was performed on Machine 1 (M1) and Machine 2 (M2), in order to asses the variation of quality characteristics values depending on machine performances [24,27].

Thermosonic wire bonding cycle is presented at Figure 1 [27]: 1. A fine gold wire is fed down through the tool called capillary; the ultrasonic transducer convert the electrical energy and transmit this resonant energy at the tip of the bonding capillary to form the gold ball; 2. Capillary moves down to the aluminium bond pad; 3. Meshed ball bond is formed at die pad, applying bond force and power; 4. Capillary lifts up and forms the looping profile; 5. and 6. Then, capillary goes down to the form the weld at the lead. This cycle is repeated until the microelectronic device is fully assembled. This paper considers optimisation of the part of wire bonding process, which refers to forming the ball band between gold wire and aluminium die pads.

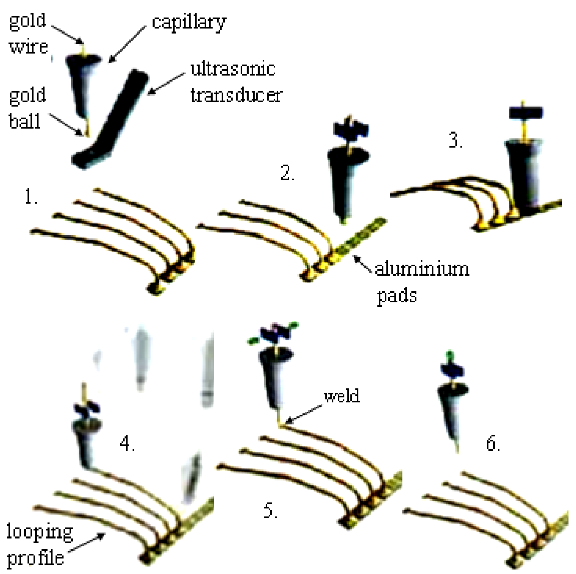

Figure 1. Thermosonic gold wire bonding cycle

3.2 Process parameters (control factors)

After formation of gold ball at the tip of the capillary, capillary moves down to the die pad applying *Base Power* and *Base Force* to form the intermetallic bond between the meshed gold ball and aluminium die pads. Hence, process parameters *Base Power* and *Base Force* were considered as control factors in the experiment. They belong to continuous type of variables. The other process parameters were not considered in the experiment, since their changes would affect the quality of the welds at the output leads. Table 1 lists the control factors and levels used in the experiment [27].

Table 1. Process parameters with different operating levels

Process parameter	Unit	Symbol	Levels		
			"1"	"2"	"3"
Base Power	mW	*BP1g*	55	65	75
Base Force	N	*BF1g*	85	100	115

3.3 Product quality characteristics (responses)

The quality of the considered part of thermosonic gold wire bonding process is characterised by the strength of the intermetallic connections between meshed gold bond and aluminium metallization at the die pads surfaces. The test performed to show the strength of the connection between gold bonds and aluminium pads is known as ball shear test. Since one microelectronic device contains several ball bonds, ball shear is performed on all ball bonds in one device. Average ball shear test value found in the device was considered as the first response. The shape and dimensions of the meshed ball bond affect the strength of gold-aluminium intermetallic connection, hence the second and third response were ball bond diameter and ball bond height, respectively. They were calculated as average values of five measurements in one device. Quality characteristics, considered as response variables in the following experiment, are: ball shear test average value (*BS*) [N], ball bond diameter (*D*) [μm], and ball bond height (*H*) [μm] (Fig. 2). It is explicit that quality characteristics *BS*, *D* and *H* are directly correlated [27].

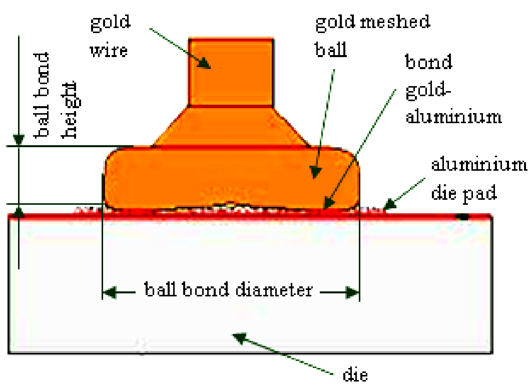

Figure 2. Meshed ball bond

Ball shear values are measured using special ball shear tester equipment. The shear tool moves horizontally parallel to the bond pad surface, shear the ball bond when the strength of the intermetallic connection is measured. Ball diameter and ball height are measured using metallographic microscope.

The gold wire diameter used for wire bonding is 75 μm in diameter; specifications limits (Lower Specification Limit – LSL, Upper Specification Limit – USL) and target values specified by customer are given in Table 2. Since the objective is to achieve the nominal value for all considered quality characteristics, all three characteristics are of the NTB type [27].

Table 2. Specification limits and target values for quality characteristics

Specifications	Ball shear test (*BS*)	Ball bond diameter (*D*)	Ball bond height (*H*)
LSL – USL	230 – 310	153 – 233	34 – 66
Target	270	193	50

3.4 Design of experiment

Since there were two control factors varied on three levels and no noise factors in the experiment, the experimental designed was based on orthogonal array L9 containing nine trials, and five repetitions were added. The experiment was performed on two machines, as explained before. The part of the experiment plan and experimental observations are shown in Table 3 [24].

3.5 Processing and analysis of experimental data

Step 1. SN ratios were computed according to (1), *MSD* values by using (2), and *QLs* by using (3).

Step 2. Transformation of *QL* values into normalised values ($NQL_i(k) \in [0;1]$) was performed by using (4), with respect to the maximal *QL* value in *k* experimental trials and the ideal case where $QL = 0$. The computed *SNs* and *NQLs* for the observed responses are listed in Table 4 [24].

Step 3. PCA was performed on *NQL* values. The principal component scores $Y_i(k)$ are shown in Table 4. Table 5 list the eigenvalues and proportions of *NQL* of each response, for the principal components [24]. All principal components were considered in this approach, in contrast to common approach where only PC_1 would be taken into account (eigenvalue greater than one), enclosing only 66.7 % of the total variance of responses for M1, and 91.5 % for M2. According to the eigenvectors from Table 5, principal component scores were computed by using following formulas, for M1:

$$Y_1(k) = 0.651\, NQL_{BS_k} + 0.523\, NQL_{D_k} + 0.550\, NQL_{H_k}$$
$$Y_2(k) = -0.033\, NQL_{BS_k} + 0.743\, NQL_{D_k} - 0.668\, NQL_{H_k}$$
$$Y_3(k) = 0.758\, NQL_{BS_k} - 0.417\, NQL_{D_k} - 0.501\, NQL_{H_k}\,, \quad (9)$$

and for M2:

$$Y_1(k) = 0.548\, NQL_{BS_k} + 0.587\, NQL_{D_k} + 0.561\, NQL_{H_k}$$
$$Y_2(k) = -0.442\, NQL_{BS_k} - 0.351\, NQL_{D_k} + 0.826\, NQL_{H_k}$$
$$Y_3(k) = -0.682\, NQL_{BS_k} + 0.730\, NQL_{D_k} + 0.054\, NQL_{H_k}\,. \quad (10)$$

Step 4. The principal component scores $Y_i(k)$ were first taken from the absolute value and then transformed into a set of comparable sequences $Z_i(k)$ by using (6). Next, the grey relational coefficient $\xi_i(k)$ was calculated by (7). Finally, the grey relational grade γ_k was computed by using (8), where the weights (proportions) ω_i are listed in the Table 5. The results of GRA are listed in Table 4 [24].

Step 5. From the value of γ_k in Table 4 and the factor levels in Table 1, the factor effects can be tabulated (Table 6). In multi-response problems, the optimal setting of each factor is the one that yields the highest multi-response synthetic performance measure.

Finally, the optimal parameter conditions obtained from the factor effects approach, for both machines, were: *BP1g* = 75 mW; *BF1g* = 1 N [24,27].

The factor effects approach discusses only discrete parameter values used in the experiment. The above set of parameters was adopted as a basis to form the initial population in GA, to find the optimal solution in continual multi-dimensional space.

Table 3. The part of experimental plan and experimental observations, for Machine 1 and Machine 2

Trial No.	Process parameter		M1: Quality characteristics			M2: Quality characteristics		
	BP1g	*BF1g*	*BS*	*D*	*H*	*BS*	*D*	*H*
1	1	1	229.56	182	58.9	232.21	180	58.7
2	2	1	260	187	54.8	262.41	188	55.8
3	3	1	266.29	193	42.6	269.49	192	44.2
…	…	…	…	…	…	…	…	…
14	2	3	277.37	201	43.3	281.74	198.5	43.85

Table 4. The SN ratios, *NQLs*, principal component scores and data of grey relational analysis, for Machine 1 and Machine 2

Trial No.	Signal-to-Noise ratios (SNs)			Normalized quality losses (*NQLs*)			Principal component scores $Y_i(k)$			$\xi_i(k)$ $i = 1, 2, 3; k = 1, .., 14$			γ_k $k = 1, .., 14$
	SN_{BS}	SN_D	SN_H	NQL_{BS}	NQL_D	NQL_H	$Y_1(k)$	$Y_2(k)$	$Y_3(k)$	ξ_1	ξ_2	ξ_3	
Machine 1													
1	-32.6842	-21.6825	89.9684	0.9604	0.8890	0.9516	1.6136	-0.0069	-0.1194	0.3449	0.9640	0.6800	0.526320
2	-25.1068	-19.2369	35.4304	0.1678	0.5062	0.3748	0.5801	0.1202	-0.2717	0.5942	0.6046	0.4830	0.587084
3	-23.2636	-12.5062	61.1104	0.1098	0.1075	0.6464	0.4832	-0.3556	-0.2855	0.6374	0.3409	0.4706	0.549952
…	…	…	…	…	…	…	…	…	…	…	…	…	…
14	-24.3861	-19.3828	52.5076	0.1421	0.5235	0.5554	0.6718	0.0133	-0.3888	0.5584	0.9327	0.3949	0.636230
Machine 2													
1	-32.1948	59.1675	86.6664	0.9884	0.8978	0.9964	1.6610	-0.0311	-0.1244	0.3333	0.3333	0.3333	1.000000
2	-24.6220	66.9864	92.1027	0.1728	0.2670	0.5629	0.5618	-0.1833	-0.2624	0.3378	0.8047	0.5868	0.373331
3	-22.8098	63.1258	92.0339	0.1139	0.1040	0.4943	0.4004	-0.2567	-0.2047	0.6013	0.4118	0.4023	0.585001
…	…	…	…	…	…	…	…	…	…	…	…	…	…
14	-24.6809	57.6587	92.1024	0.1752	0.2094	0.4854	0.4905	-0.1744	-0.1977	0.5941	0.4075	0.3422	0.576955

Table 5. Results of PCA performed on NQL_{BS}, NQL_D and NQL_H, for Machine 1 and Machine 2

	Machine 1			Machine 2		
Principal Components	PC_1	PC_2	PC_3	PC_1	PC_2	PC_3
Eigenvalues	2.0014	0.7371	0.2615	2.7438	0.1981	0.0581
Proportions	0.667	0.246	0.087	0.915	0.066	0.019
Eigenvectors						
NQL_{BS}	0.651	-0.033	0.758	0.584	-0.442	-0.682
NQL_D	0.523	0.743	-0.417	0.587	-0.351	0.730
NQL_H	0.550	-0.668	-0.501	0.561	0.826	0.054

Table 6. Summary of factor effects, for both machines

Levels	Control factors (process parameters)			
	Machine 1		Machine 2	
	BP1g	*BF1g*	*BP1g*	*BF1g*
1	0.5500	0.5266	0.5502	0.5763
2	0.5597	**0.5845**	0.6255	**0.6336**
3	**0.5941**	0.5802	**0.6360**	0.5978

3.6 Process modelling and optimisation

Step 1. The set of BP ANN were trained in order to model the relationship between synthetic performance measure γ_k and process parameters, for M1 and M2 separately. Each of the developed networks has two neurones in the input layer corresponding to two process parameters, and one neurone in the output layer corresponding to a single synthetic multi-response performance measure. The number of neurones in the hidden layer varies from 1 to 9. The results of training of ANNs are presented in Table 7 [24].

Step 2. From the data in Table 7, the network topology 2-9-1 showed the least error for both machines (*MSE* = 0.00018873 for M1, and *MSE* = 0.00014759 for M2) and therefore they were selected to present the process model (Fig. 3). The presentation of the training, validation and testing process of the selected 2-9-1 networks are displayed at Figure 4 for M1 and Figure 5 for M2 [24].

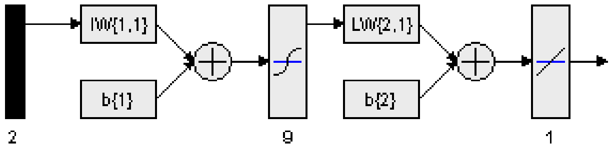

Figure 3. Topology of the selected ANN models (2-9-1)

Step 3. The selected networks present an objective functions for GA, for M1 and M2 separately. Nine different GAs were developed for each machine; the initial population was seeded close to the set suggested by the factor effects approach; population size was 10. Since experimental results showed that high value of *BF1g* is favourable for achieving high synthetic performance measure, the upper bound for *BF1g* was extended to 85 mW in GA. The results of GAs are presented in Table 8 [24].

Step 4. For M1, GA 1 and GA 4 resulted with the equally best fitness value (γ = 0.88120) and off-line performance, giving the optimal parameters setting: *BP1g* = 85 mW; *BF1g* = 0.99 N.

The equally best results in terms of fitness value (γ = 0,71277) and off-line performance showed GA 2 and GA 5 for M2, giving the optimal parameters setting: *BP1g* = 85 mW; *BF1g* = 0.95 N [24].

Table 7. Results of ANNs training (*MSE* and *R* values for ANNs with different topology), for Machine 1 and Machine 2

Topology of ANN		2-2-1	2-3-1	2-4-1	2-5-1	2-6-1	2-7-1	2-8-1	**2-9-1**
Machine 1	*MSE*	0.00033987	0.00028367	0.00031174	0.00031720	0.00028620	0.00023881	0.0002399	**0.00018873**
	R	0.9482	0.9553	0.9690	0.9710	0.9645	0.9701	0.9653	**0.9717**
Machine 2	*MSE*	0.00040726	0.00020155	0.00030591	0.0001907	0.00026473	0.00023374	0.0002297	**0.00014759**
	R	0.9568	0.9674	0.9721	0.9376	0.9639	0.9548	0.9682	**0.9717**

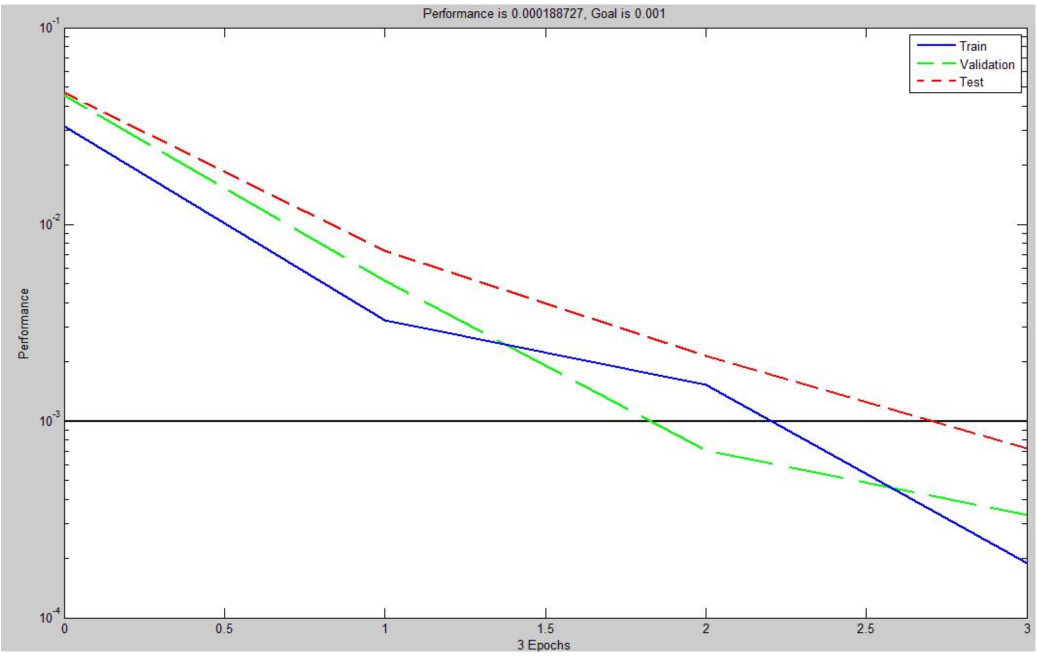

Figure 4. Convergence (*MSE* vs. learning iterations) of the selected ANN (2-9-1), for Machine 1

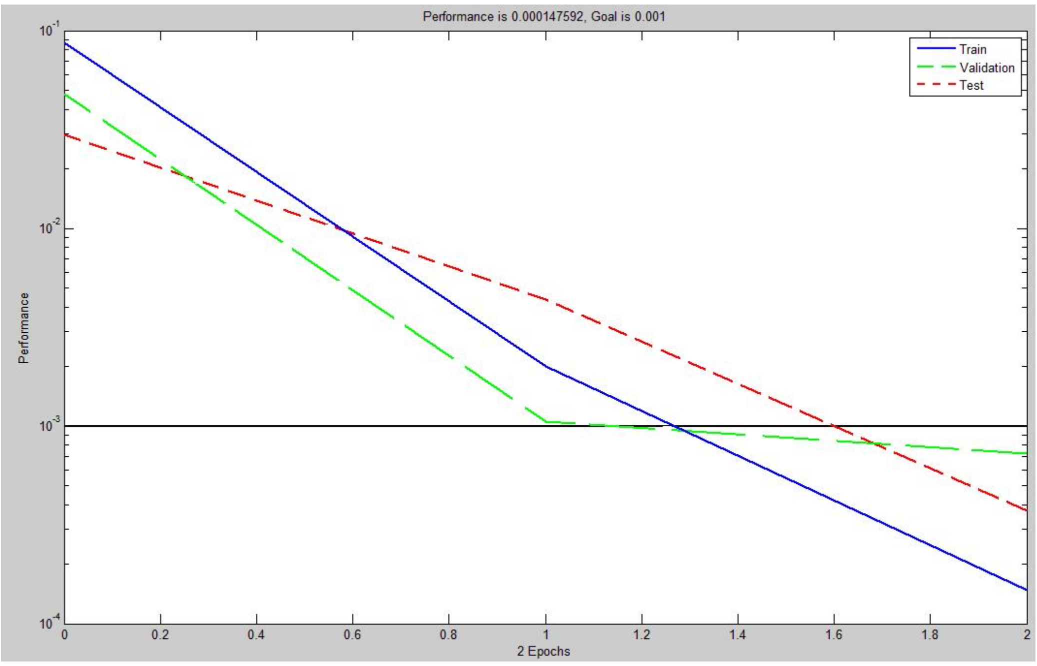

Figure 5. Convergence (*MSE* vs. learning iterations) of the selected ANN (2-9-1), for Machine 2

Table 8. GAs settings and results, for Machine 1 and Machine 2

GA		GA 1	GA 2	GA 3	GA 4	GA 5	GA 6	GA 7	GA 8	GA 9
Selection function		stochastic uniform	roulette wheel	tournament	stochastic uniform	roulette wheel	tournament	stochastic uniform	roulette wheel	tournament
Crossover function		single point			two point			arithmetic		
Machine 1										
Fitness function		**0.88120**	0.88088	0.88070	**0.88120**	0.88087	0.88070	0.88075	0.88076	0.88070
Off-line performance		0.88120	0.88088	0.88070	0.88120	0.88087	0.88070	0.88075	0.88076	0.88070
Optimal set	*BP1g*	**85.00**	85.00	85.00	**85.00**	85.00	85.00	85.00	85.00	85.00
	BF1g	**98.97**	99.81	100.00	**98.96**	99.83	100.00	99.95	99.95	100.00
Machine 2										
Fitness function		0.70823	**0.71277**	0.70807	0.71009	**0.71277**	0.70807	0.70811	0.70810	0.70807
Off-line performance		0.70822	0.71275	0.70807	0.71009	0.71275	0.70807	0.70811	0.70810	0.70807
Optimal set	*BP1g*	85.00	**85.00**	85.00	85.00	**85.00**	85.00	85.00	85.00	85.00
	BF1g	99.75	**94.96**	100.00	96.97	**94.96**	100.00	99.94	99.96	100.00

3.7 Discussion

The analysis of implementation of the proposed approach was performed comparing to RSM and the factor effects application. In RSM application, the superpositioned plot was formed by superposing contour plots for all responses, in order to find the specific area on the superpositioned plot that meets specifications for all responses. The correlations among responses were not discussed in RSM application [27].

Table 9 provides a comparison of the synthetic performance measure γ and optimal parameters setting obtained from three methods of the analysis. It can be seen that the factor effects approach, that considers correlations among responses, showed better results (γ) than RSM method [27]. The application of the proposed intelligent approach resulted in a better solution (in term of synthetic performance measure) than the factor effects, due to search over continual space [24].

From Table 8 it is visible that all tested GAs show similar results in terms of fitness function values (γ) and optimal parameters setting for M1. However, for M2, the significant difference in *BF1g* values obtained from different GAs could be noticed. It could be seen that "tournament" selection gave the lowest fitness function values. Also, GA 8 with "arithmetic" crossover show significantly lower fitness function than other two GAs (GA 2 and GA 5) that use the same selection ("roulette wheel"). Hence, it could be concluded that the "tournament" selection and the "arithmetic" crossover are not adequate for the observed problem. It could be also concluded that the "roulette wheel" selection is appropriate for this problem. This proves the necessity to consider different GA's basic functions, for each optimisation problem [24].

Initial population for both machines was formed close to the set suggested by the factor effects approach. For M1, all GAs converged to the optimal solution in the first ten generations, which is the consequence of a good-seeded initial population. If initial population was not set properly, the algorithm would need more time (generations) to find the actual optimal solution. For M2, GA 2 converged to the best solution in the 1050-th generation and GA 5 in the 710-th generation (from 2000 generations in total). This could mean that, when the selection is "roulette wheel", the crossover "two point" (GA 5) converges faster than "single point" function (GA 2) [24]. The observed difference in a speed of convergence of GAs between M1 and M2 could be explained by the set of input data for GA and ANN. The above difference in GAs convergence between Machine 1 and Machine 2 proved the initial indication that interrelations between process parameters and responses on Machine 2 are more complex, containing more noise effects, than on the other machines used for this process [24]. This could be also the cause of the difference in the best achieved synthetic multi-response performance measure between M1 and M2 (Table 9).

Table 9. Comparative analysis of optimal parameter settings obtained by different methods, for both machines

Method	RSM		The factor effects approach		The proposed approach	
	M 1	M 2	M 1	M 2	M 1	M 2
[*BP1g*; *BF1g*]	[65; 100]	[65; 100]	[75; 100]	[75; 100]	[85; 99]	[85; 95]
γ	0.6303	0.6379	0.6395	0.6463	0.8812	0.7127

Finally, the established process parameters window for the considered part of the process is: *BP1* = 85 mW, *BP1* = 0.95 – 0.99 N. This set is adopted as a final solution of the observed multi-response problem.

4. CONCLUSION

The majority of today's industrial products are defined by several quality characteristics, hence the multi-response process optimisation has become an increasingly important and demanding task.

This research is based on the Taguchi static robust parameter design, employing PCA and GRA to consider correlations among responses and to obtain single multi-response performance statistic for multi-response process optimisation. The process modelling is performed using BP ANN, presenting an input for GA. GA finds the optimum setting of the process parameters that simultaneously meet the specifications of all responses, where the solution is not constrained by the process parameter levels used in experimental trials.

The major advantages of the presented generic and intelligent method for multi-response process optimisation for correlated responses are [24]:

- By using Taguchi's SN ratio and quality loss, relative significance of responses are adequately represented and the response mean and variation are assessed simultaneously [15,27,28];
- Multivariate statistical methods PCA and GRA are employed to uncorrelate and synthesise responses, ensuring that the weights of responses in synthetic performance measure are based on the total variance of the original data, which results in improved objectivity of the analysis [15,27,28];
- By using a single performance statistic, procedure of developing and training of ANNs is simplified, as well as the implementation of GA;
- The GA's capacity of performing global search among all possible solutions in continual multi-dimensional space ensures convergence to the global optimal parameter settings. In the presented approach, the initial population in GA is formed in the neighrbourhood of the potentially good solution (the parameter settings obtained by the factor effects approach). This feature advances the convergence to the global solution, meaning that the probability of finding the actual global solution in the given number of generation is significantly improved;
- The proposed method does not depend on the type of the process, type of relations between responses and process parameters, type and number of process parameters and responses, existence of correlations between responses or process parameters, or their interrelations, thus making its application convenient for broad spectrum of static optimisation problems.

The analysis of several experimental results confirms the effectiveness of the presented method and emphasises universality of its application for static multi-response problems [24]. Analysis of the application of the proposed method on the here-observed experimental study and its comparison with other two methods for multi-response optimisation showed that the proposed approach can yield to a better solution in terms of optimal parameters setting and synthetic multi-response performance measure.

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НОВИ ПРИСТУП ОПТИМИЗАЦИЈИ ПРОЦЕСА ЗА ВИШЕ МЕЂУЗАВИСНИХ ИЗЛАЗА

Татјана В. Шибалија, Видосав Д. Мајсторовић

Рад представља нови, општи и интелигентни приступ оптимизацији процеса са више излаза, чија је сврха добијање јединственог оптималног скупа параметара процеса који задовољава спецификације за све излазе, који могу бити у корелацији. Приступ је базиран на Тагучијевој функцији губитка квалитета, статистичким методама: анализа главних компоненти и анализа релација са шумом, и техникама вештачке интелигенције: вештачке неуронске мреже и генетски алгоритам. Предложени модел разматра оптимизацију процеса у општем случају када су аналитичке релације и међузависности у процесу непознате, тиме чинећи модел применљивим за различите врсте проблема оптимизације процеса. Имплементација предложеног приступа је представљена на студији која разматра оптимизацију процеса термосоничног повезивања златном жицом у полупроводничкој индустрији, за повезивање микроелектронских уређаја. Резултати потврђују успешност овог приступа у присуству три међузависна излаза (карактеристике квалитета производа).