ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 1, Issue 2, November 2012

Optimization of Process Factors in Super capacitor Fabrication Using the Genetic Algorithm to Optimize Taguchi Signal-to-Noise Ratios

Chia Yen Yee, Ridhuan Ahmad Samsuri, Dino Isa, Ahmida Ajina, Khiew Pooi Sim
keyx1cyy@nottingham.edu.my, kecx1ram@nottingham.edu.my, kezdi@nottingham.edu.my, keyx7aaj@nottingham.edu.my, efzpsk@nottingham.edu.my
Department of Electrical and Electronic Engineering University of Nottingham Malaysia Campus,
Department of Electrical and Electronic Engineering University of Nottingham Malaysia Campus,
Department of Electrical and Electronic Engineering University of Nottingham Malaysia Campus,
Department of Electrical and Electronic Engineering University of Nottingham Malaysia Campus,
Foundation Studies in Engineering and Computer Science of University of Nottingham Malaysia Campus

Abstract*— This paper proposes an approach which deals with the optimization of process factors for super capacitor fabrication. The methodology developed here is useful for solving multi response problems in a manufacturing environment. A way of implementing the proposed approach for fabrication of coin-type super-capacitors is presented. The Taguchi method is combined with a Genetic Algorithm (GA) in order to optimize a weighted signal-to-noise ratio (WSNR) which is essential in identifying the most robust process factors. Consequently, the GA is used to enhance the WSNR value and thus to maximize the strength of the signal over noise. Experimental result shows that the proposed approach has the potential and ability to solve multi response problem for this domain. A comparison of the results achieved using the GA and the result from the Overall Evaluation Criteria (OEC) is made based on the improvement of the SNR (in dB) and the standard deviation. Finally, variance analysis plays an important role in identifying the most statistically significant factors in the process. The main contribution of this approach is to effectively and efficiently tackle multi response problem involved in the fabrication of super-capacitors where the values of both Capacitance and Equivalent Series Resistance (ESR) are equally important.

***Index Terms*— Genetic Algorithm; Multi Response Problem; Process Optimization; Super Capacitors; Taguchi Method.**

I. INTRODUCTION

Previous applications [1] – [4] indicate that the Taguchi method emphasizes the solution of single-response problems with the aid of knowledge gained from past experience. Thus, it is not capable of handling multi response problems without requiring some modifications in the application. The Taguchi method provides practitioners and designers with a systematic approach for conducting experiments to obtain near optimal settings of design factors for performance and cost [5] – [7]. The design (controllable) factors and noise (uncontrollable) factors, which influence the quality of the product, are considered together instead of individually [3] [4] [8].

The objective of implementing the Taguchi method is to obtain the best combination of factors and levels in order to achieve the most robust product. This means, the selected levels of the various design factors from the Taguchi method allows the performance of the product/process to be less sensitive to the noise factors.

However, in today's manufacturing environment, many processes or products involve solving multi response problem to improve their product quality. One crucial fact is that the Taguchi method is incapable of performing well for multi-response optimization problem [5] [6]. In order to overcome this limitation, we have formulated a way to include a GA within the Taguchi method. A common method of solving the multi response problems is to assign each response with a weight, as mentioned in [5] [6] [9]. A normal question which arises is how to determine and define the weight for each response in a real case. The goal of this proposed strategy is to ensure that the performance characteristics (or the quality) have minimal variation while having its mean close to the desired target value.

The idea underlying this integrated strategy is to convert the problem of optimizing a complicated multi process response into one that optimizes a single weight of the SNR. This means, the WSNR is used in the overall evaluation of experimental data in the multi response optimization problem. In this case, the GA strategy utilizes the normalized SNR (Z) from the Taguchi method to form its fitness function. The optimal level for each individual process factor is the level with the highest WSNR. This paper is organized as follows. Research methodology is presented in Section 2, which shows the background theories used in this research. Section 3 illustrates the proposed integrated strategy. The coin super capacitor fabrication process is the illustrative example given in this paper. Analysis of variance (ANOVA) is also applied to identify the most critical factors that influence WSNR. In Section 4, results and discussions are presented where a set of OEC based on the engineering judgment result is compared with the set of results obtained from the proposed integrated strategy. Confirmations of the results obtained from experiments are presented in Section 5. Section 6 concludes the paper.

II. Research Methodology

A. *The Taguchi Method*

Design of experiments (DOE) is a method that can be used to identify the critical areas that cause yield loss in a process. With proper application of DOE, design engineers or researchers are able to pinpoint the source of the yield problem and fix them to produce solid and robust designs with much higher yield [10]. In DOE, the three terms that need to be clearly defined are Factors, Levels and Replication. Factors or parameters are important variables that would affect the outcomes or output responses. However, all factors may not have equal importance as some factors may have a more prominent effect over other factors. "Levels" in the simplest terms are possible values for each factor identified thru gathered data (for this case the levels are "low" and "high"). For example, if two levels are assigned to each factor, one of the lower levels is a lower level and the other is a higher level. The values of these levels are assigned in reference to literature, consultation with experts or one can identify level values thru experimentation before the Taguchi method is carried out [1] [11]. A two-level factor assumes linear behavior while three-level factor best fits non-linear behavior but requires a larger number of trials while running experiments. Replication is necessary to address the concern on repeatability and also the spread of the variation in the experimental outcome. This is done in order to obtain adequately accurate statistical information of the process under study. This is done by producing several samples for each trial or by repeating the same trial several times.

The Taguchi method is famous for implementing robust (parameter and tolerance) design. Robust design is a result of determining the optimal factor combination/setting to reduce the response variation and brings the mean close to the target value consequently [12]. To implement the robust design, Taguchi employs an orthogonal array (OA) in order to reduce the number of experiments as compared to the full factorial DOE version. SNRs are used to evaluate the outcome of the experimental trials. The details of the SNR calculations are covered in section 3.1. It is common to include an ANOVA alongside SNR to study the percentage contribution made by each factor. Even though the Taguchi method has been successfully applied to processes in design and manufacturing, it has been criticized for its lack of efficiency because the method works well for single-objective optimization problems but not for multi-objective problems [1] [13]. Some modification on the existing method has to be made [6] [14] - [16] to make it work for some cases of multi objective problems. Similarly, the Taguchi method for multi-objective problems, as discussed by Phadke (1969) [15], is purely based on judgmental and subjective process knowledge [17].

When dealing with a multi-objective problem, one can use several techniques. The simplest way is by adopting the OEC (overall evaluation criteria) approach. This is done by assigning certain weighting to each of the output response criteria so as to normalize the two (or more) different response units. The weightings are arbitrarily chosen based on experience in order to make a response either dominate or have the same weight when compared to the other responses [10] [18] – [20]. Such judgments are not very accurate [17]. A way of overcoming this problem is by using the GA approach. In Section 2.2, the GA method will be further discussed specifically on how it was used with the Taguchi method to make solving the multi-objective problem possible. The GA will search for the optimal weights that maximize the SNR for each output response to improve its immunity to noise and thus make the product more robust. The hypothesis here is that the GA approach will result in a better SNR as compared to the OEC (initial method as stated table 9) method because the GA searches the entire solution space for the optimal point whereas the weights determined by experience does not. To proof this hypothesis, the percentage improvement of the SNR (if any) will be determined and then the process parameters will be implemented to confirm the increase in robustness of the product.

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 1, Issue 2, November 2012

B. *Genetic Algorithm (GA)*

The main aim of integrating the GA into the Taguchi technique is to search for definite and optimal weights for each response (or performance characteristic and quality) in a multi-response system. As previously stated [1] [3] [4] [8] [9], the Taguchi method has been mostly utilized in optimizing single-response problems. One of the noted methods in tackling multi response systems is the problem of optimizing weights for signal to noise ratio as mentioned in the literature [1] [4]. In real multi-response cases as described in [1] [21], the weights are based on experience. For instance, in the OEC approach the relative weighting method is used to tackle problems with more than one objective [8]. The method of combining multi criteria of evaluation is truly based on the expertise and the experience gained in many experiments. However, in most real cases this does not result in a robust process or product. This might be due to a level of uncertainties in the decision-making stage especially when picking levels for the parameters. Furthermore, it is difficult for human experts to estimate the affect of the criteria used to evaluate a process as not all criteria have equal importance. As such, the key of obtaining a robust and practical process using this weighting method may be to eliminate the engineering judgment in deciding the weights (or the importance) of the criteria.
The GA is a powerful heuristic global search and optimization technique. It is an optimization technique which is built based on mimicking the evolutionary principles and chromosomal processing in natural selection and natural genetics [22] – [24]. It is a widely accepted approach to stochastic optimization, especially in dealing with a global optimization problems that consists of multi-modal search spaces. In a wider usage of the term, GA is any population-based model that uses selection and recombination operators to generate new sample points in a specific search space [25]. In his book [22], Goldberg demonstrated the possible domains where GA's can be applied. Moreover, many GA models have been introduced by researchers and are found to be effective from the experiment perspective [24] [25]. In addition, many of them are application oriented and have adopted GA's as optimization tools [6] [24] [25] [29]. The searching and selection of optimal weights for the process of fabrication of super-capacitors using the Taguchi method often involves problems related to constrained optimization which is similar to what is needed in manufacturing process optimization. Hence, it is appropriate that GA's are integrated with the Taguchi method to optimize the fabrication of coin-type super-capacitors. The capacitance and equivalent series resistance (ESR) of the device are adopted as the quantitative performance characteristic (quality) for evaluation in the current study.
GA's basically evolved from an idea of survival of the fittest and reproduction of new offspring to form a new population to create a novel and innovative search strategy [6] [25]. It implies that the genetic pool in GA of a given population potentially contains the solution, or a better solution, to a given adaptive problem [25] [26]. This makes the GA different as compared to other traditional point-to-point descending and ascending search techniques [28]. The GA initiates from a random set of solutions, known as the initial 'population'. Each individual solution in the population is known as a 'chromosome' (or string). At each generation, the GA works with genetic operators namely crossover and mutation, on the selected individuals which act as parents to recombine part of the strings (genes) and produce offspring (child) to create a new and hopefully fitter generation [22] [24] [26] [27]. During each generation, these chromosomes evolve to have better fitness. This is done by executing an operation known as selection. Eventually, the chromosomes in the population will converge from generation to generation. The aim is to select the best fit chromosome [6] [22] [26] [27]. By fulfilling the aim mentioned, GA utilizes the fitness function (or objective function) which will be used to create a new and conceivably better population of strings. The fitness function takes a chromosome and assigns a relative fitness value to the chromosome [22]. The fitness function evidently ranks the chromosome in some way by producing fitness values [26] [27]. The procedure for the application of Taguchi and GA to solve multi response problems is presented in section 3.

III. THE PROPOSED INTEGRATED STRATEGY – A CASE STUDY ON THE PROCESS FABRICATION OF COIN-TYPE SUPERCAPACITOR

In this particular case study, coin-type super capacitor is subjected for Taguchi-GA process optimization. The integrated approach is divided into several repeatable steps that could also be applied in other process/product multi-objective optimization problem accordingly. There are four steps outlined (Step 1-4) for the initial experimental factors and levels design, including the computation of SNRs from the experimental data. Next, the integration of GA approach for determining the optimal weights based on the normalized SNRs (Z) in the range between zero and one are conducted (Step 5-6). The WSNR is then computed by multiplying the weight with Z relates to each response. The final two steps (Step 7-8) will be the data analysis focusing on the main effect of each factor towards the WSNR values, which is essential for predicting the desired optimal setting. It continues with the

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
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confirmation experiments. Consequently, further statistical data analysis includes the measure of variability between OEC and the proposed strategy is conducted using standard deviation and ANOVA, in order to determine the percentage improvement acquired (if any) and subsequently identify the dominant factors that influencing the capacitive performance of the device.

A. *DOE (Steps of the method applied, the equation of SNR, Z)*

The steps fall within the initial experimental design stage, are listed as follows:
Step 1: Assigning factors and levels for each of the main processes.
Table 1 provides the lists of control factors for process optimization of the mixing, calendaring, drying and electrolyte treatment process. All of the three factors (A, B and C) are assigned with two levels each for the experiment.

Table 1 .Process Factors And Their Levels For The Super capacitors Fabricated

Process		Factors	Level 1	Level 2	Output Response
1 Mixing	A	Mixing Speed (rpm)	200	350	1. Capacitance (F).
	B	Mixing Time (min)	15	30	2. ESR (Ω).
	C	Amount of AC (%)	85	90	
2 Calendaring	A	Calendaring time (min)	15	30	
	B	Thickness (mm)	0.65	0.85	
	C	Machine temp. (^oC)	23	30	
3 Drying	A	Heating time (min)	20	45	
	B	Heating temp. (^oC)	50	80	
	C	Vacuum	Yes	No	
4 Electrolyte Treatment	A	Electrolyte name	KCl	Na_2SO_4	
	B	Electrolyte molarity (M)	2	3	
	C	Electrolyte amount (ml)	0.5	0.8	

Step 2: Determining the minimum number of experiments required and the selection of Taguchi orthogonal array. Here, the Taguchi multi-objective optimization begins with the selection of orthogonal array with specific number of levels (L) for A, B and C. The minimum number of experiments in the array is obtained by:

$$N = (L-1)F + 1 \quad (1)$$

where F= number of factors=3
Thus, L_4 orthogonal array is selected due to four numbers of trials required and outlined as in Table 2.

Table 2 .4 X L_4 Orthogonal Arrays for the Process Factors

Process	Experiment, *i*	A	B	C
1 Mixing	1	1	1	1
	2	1	2	2
	3	2	1	2
	4	2	2	1
2 Calendering	1	1	1	1
	2	1	2	2
	3	2	1	2
	4	2	2	1
3 Drying	1	1	1	1
	2	1	2	2
	3	2	1	2
	4	2	2	1

ISSN: 2319-5967
ISO 9001:2008 Certified
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4	**1**	**1**	**1**	**1**
Electrolyte	**2**	**1**	**2**	**2**
Treatment	**3**	**2**	**1**	**2**
	4	**2**	**2**	**1**

Step 3: Conducting all experiments outlined with three replications (samples) each.
Step 4: Computing SNR for every output responses.
The SNR values for the respective responses (SN_{iC} and SN_{iE}) are calculated from the raw data accordingly.
SNR for the capacitance response (larger-the-better);

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

SNR for the ESR response (smaller-the-better);

$$SN_{iE} = -10 \log_{10}(1/n) \sum_{i=1}^{n} {y_i}^2 \quad (3)$$

where y_i is the experimental data at the *i*th sample and n is the number of samples.

B. *The Integrated Taguchi method with GA*

Step 5: Normalizing the SNRs so that all are in the range between 0-1.
Normalized y_{ij} as Z_{ij} [0, 1] by the corresponding formula to set the right effect of adopting different units:
Normalized SNR for the capacitance response (larger-the-better);

$$Z_{iC} = (Y_{avg.} - Y_{min})/(Y_{max} - Y_{min}) \quad (4)$$

Normalized SNR for the ESR response (smaller-the-better);

$$Z_{iE} = (Y_{max} - Y_{avg.})/(Y_{max} - Y_{min}) \quad (5)$$

where Y_{avg} is the average out of the n number of samples produced, Y_{min} and Y_{max} are the least and highest data value out of the n number of samples produced respectively.

Step 6: Searching for the exact/optimal weighting value w associated with each Z that would give the maximum WSNR by using GA approach.
The WSNR value is determined by using the weights (w_c and w_E) obtained from GA.

$$WSNR_i = w_C \mathbf{Z_{iC}} + w_E \mathbf{Z_{iE}} \quad (6)$$

In the GA approach of solving an optimization problem, the operation is summarized as follow:

Initialization

The algorithm is carried out randomly to create the solution space which is used for searching the optimal weights so as to maximize Z. In this coin super capacitor fabrication process, we have two output responses; hence there are only two weights which are considered as the gene. The initial population composes of 30 chromosomes. The 30 chromosomes in the initial population are generated subject to the feasibility condition, i.e. the sum of weights should always equal to one.

The Fitness Function

The total WSNR is used as the fitness function in GA strategy to calculate the fitness value. A fitness value in an objective function evaluates the performance level of an individual chromosome; therefore in this case, GA strategy utilizes Z from Taguchi method to form this fitness function. The particular fittest chromosome will be ranked against all other individual chromosomes. The fitness function is given as:

$$f(x) = \sum_{j=1}^{k} \sum_{i=1}^{n} (W_j Z_{ij}) \quad (7)$$

The above equation is written such that $f(x)$ is the total WSNR to be maximised, w_{ij} is the weight to each response, Z_{ij} is normalized SNR values, n is numbers of observation (experiments/runs) and k is the number of response.

Selection

Selection is also known as reproduction in the family of computational model inspired by evolution [24] [26] [27]. It allows individual string (chromosome) to be copied for possible inclusion in the next generation. The chance that a string will be copied is based on the string's fitness value which is calculated from the fitness function. For each generation, Selection chooses strings that are placed into the mating pool, which is used as the fundamental to create the next generation. Parent chromosomes are selected with a probability related to their fitness value. Therefore, highly fit strings possess the higher probability of being selected for mating [25]. In this supercapacitor fabrication process, the roulette wheel method is applied to the chromosome selection.

Crossover

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
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Once the mating pool is created using Selection operator, the next operator is the crossover. The term 'Crossover' used in GA is analogous to reproduction and biological crossover. 'Crossover' is used to create a pair of offspring chromosome from the parent chromosome [25]. Crossover takes place by depending on the parameter known as the crossover probability, P_c [1]. If the crossover does not take place, two selected chromosomes are simply copied to the new population. The concept of this operator is the new chromosome may be better than both of the parent chromosomes as the offspring takes the goodness from each of the parents.

Mutation

One-gene mutation operation with a preset mutation probability P_m which indicates the frequency at which mutation occurs is applied to generate a new chromosome [1]. P_m should be preset at a very low value. In this case, mutation is performed during the crossover. Mutation occurs when a new gene's value is added to the new population pool. This is to avoid the population stagnating at any local optima [25].

Check for feasibility

This is an extra step to obtain reliable weights of the fitness function. In this case, this step is crucial to ensure that the sum of the weights is always equal to one. This step is to encounters 3 possible cases mentioned below.

***Case 1* - the sum of the gene values of offspring is less than one.**

For example,

If the sum of the gene values of offspring is 0.9; there is a shortage quantity of 0.1 (since 1 -0.9 = 0.1). The shortage quantity will be equally divided, and added equally to the gene values.

***Case 2* - The sum of the gene values of offspring is more than one.**

For example,

If the sum of the gene values of offspring is 1.2, there is an excess quantity of 0.2 (since 1.2 – 1.0 = 0.2). The excess quantity will be equally divided, and added equally to the gene values.

***Case 3* - The sum of the gene values of offspring equal to one, the gene values will remain the same.**

Stopping Condition

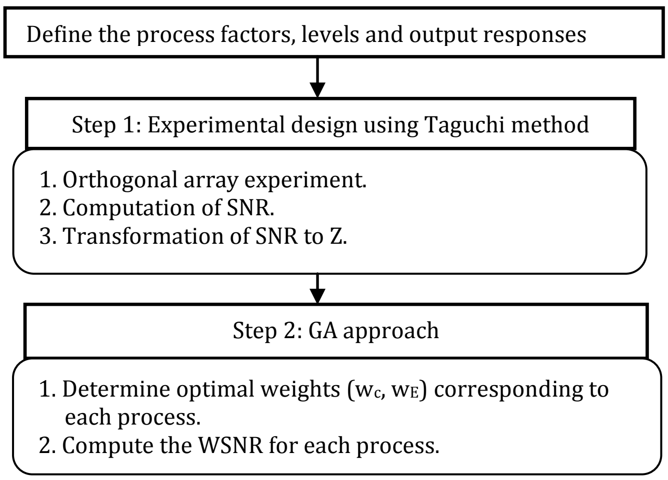
The most usual and popular method – setting the maximum number of generation is used for the stopping condition. This can guarantee the convergence of a GA. In this case, the stopping condition is the total number of generations fixed at 10,000 [1] [22].

Step 7: Study the main effects on WSNR for each factor and level by plotting the Factor Effects on WSNR graphs. This will lead to our predicted optimal conditions.

WSNR is similar to the overall evaluation of experiment (OEC) data for a multi-response process but the weightings used are the main difference. The Table 6 depicts the main effect on the WSNR. The level with the highest WSNR is the optimal level of process factors. The computation of the main effect on WSNR is carried out by considering the average effect of each level with respect to each factor.

$$A_1 = (WSNR_1 + WSNR_2) / 2 \quad (8)$$
$$A_2 = (WSNR_3 + WSNR_4) / 2 \quad (9)$$
$$B_1 = (WSNR_1 + WSNR_3) / 2 \quad (10)$$
$$B_2 = (WSNR_2 + WSNR_4) / 2 \quad (11)$$
$$C_1 = (WSNR_1 + WSNR_4) / 2 \quad (12)$$
$$C_2 = (WSNR_2 + WSNR_3) / 2 \quad (13)$$

Step 8: Running the confirmation experiment and compare the results (Standard Deviation and SNR) with the earlier trials and initial conditions.



ISSN: 2319-5967
ISO 9001:2008 Certified
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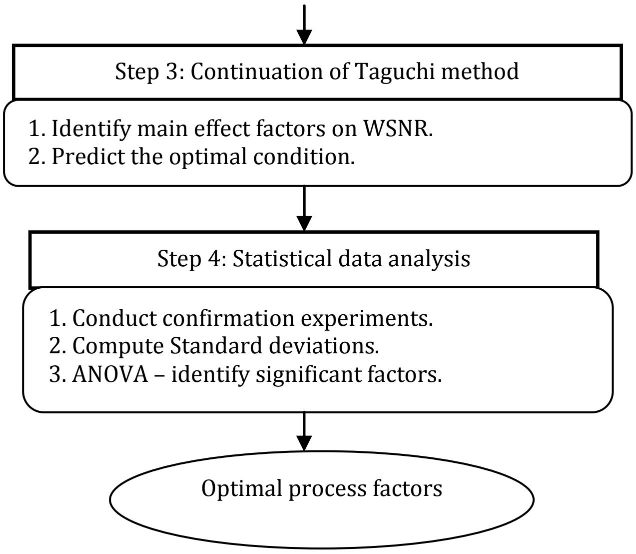

Fig. 1. The Proposed Integrated Approach

IV. RESULT AND DISCUSSION

According to L4 orthogonal array, all the trials were conducted and the results are shown in the Table 3. Three samples were produced for each run and their capacitance and ESR performance were tested using an Autolab Potentiostat (PGSTAT302N) under cyclic voltammetry and galvanostatic charge-discharge tests respectively. Table 4 summarizes the transformation values of raw data from the Table 3 into SNR and *Z*, before finally using the optimal weight of w_c and w_E found from GA method to determine the WSNR.

Table 3 .Experimental Output Data

Process	Experiment, i	Response 1- Capacitance (F)			Response 2 - ESR (Ω)		
		1	2	3	1	2	3
1 Mixing	1	0.989	1.074	1.105	12.15	19.05	18.45
	2	1.942	2.070	2.074	12.80	4.70	14.15
	3	2.231	2.441	2.399	3.20	6.60	2.00
	4	1.624	1.675	1.820	9.05	17.45	11.20
2 Calendering	1	2.035	2.039	2.132	2.30	3.50	3.15
	2	2.583	2.440	2.654	2.35	2.05	3.20
	3	1.967	1.901	1.979	2.85	2.06	2.35
	4	2.140	2.173	2.406	2.25	3.00	2.95
3 Drying	1	2.295	2.462	2.409	2.85	2.50	2.55
	2	2.558	2.317	2.680	2.30	2.90	2.75
	3	2.681	2.338	2.578	2.70	2.95	2.30
	4	2.448	2.581	2.459	2.45	2.50	2.70
4 Electrolyte Treatment	1	1.757	1.901	1.653	3.35	2.85	3.00
	2	2.457	2.590	2.468	2.56	2.61	2.81
	3	1.622	1.598	1.605	5.10	6.45	4.25
	4	2.293	2.556	2.558	2.40	2.50	2.30

Table 4 .Weighted SNR (WSNR) Values

Process	Experiment, i	$(SNR)_{ic}$	$(SNR)_{iE}$	Z_{ic}	Z_{iE}	$WSNR_i$
1 Mixing	1	10.03	-24.53	0.578	0.362	0.5778
	2	15.69	-21.22	0.656	0.393	*0.6557*
	3	16.99	-12.85	0.600	0.580	0.5998
	4	14.19	-22.32	0.420	0.581	0.4202
2 Calendering	1	15.85	-9.62	0.3471	0.4306	0.3484
	2	17.71	-8.23	0.5561	0.3333	0.5526
	3	15.34	-7.75	0.6154	0.5443	*0.6143*
	4	16.56	-8.80	0.3747	0.3556	0.3744
3 Drying	1	17.11	-8.43	0.5609	0.6190	0.5612
	2	17.58	-8.50	0.5546	0.4167	0.5539
	3	17.63	-8.51	0.5666	0.4615	*0.5661*
	4	17.45	-8.14	0.3609	0.6000	0.3621
4 Electrolyte Treatment	1	14.52	-9.75	0.4731	0.5667	0.5649
	2	17.52	-8.50	0.3609	0.6000	*0.5953*
	3	13.67	-14.55	0.4306	0.5379	0.5358
	4	16.34	-7.61	0.6642	0.5000	0.5032

From GA, optimal weights for each response are obtained in order to maximize the values of SN ratio. For example, in Process 1 w_c and w_E were found to be 0.9990 and 0.0001 respectively. The following result was obtained as optimal weight corresponding to each response. The optimal weights are [0.9990, 0.0001]. Thus, the particular solution for WSNR from eq. 6 is given by;

$$WSNR_i = 0.999Z_{iC} + 0.0001Z_{iE} \qquad (6)'$$

The corresponding values of w_c and w_E for the rest of the other processes are shown in Table 5.

Table 5. Results Obtained From GA Approach

Process	w_C	w_E
1	0.9990	0.0001
2	0.9844	0.0156
3	0.9951	0.0049
4	0.0196	0.9804

After all of the WSNR values for each trial and each fabrication process were computed (by substituting the w_C and w_E values into the WSNR formula) it was noticed that in Process 1 (mixing), Run 2 has the highest WSNR value. If we refer back to Table 2, it corresponds to A1, B2, C2 as the desired setting. However, this approach is less accurate as the interactions between factors and levels have not yet been taken into account. The same can be implied for the rest of the Processes (2, 3 and 4). A better approach is to evaluate the factor main effects on WSNR. The simple calculations of Equation (8-13) were performed to obtain the average WSNR that indicates the effect on the low and the high level for each factor. The higher the difference between the minimum (low level) and maximum (high level) is, the greater the effect it will have. Table 6 provides the details of the main effects on WSNR.

Figure 2 consists of four sets of the main effect plot for the respective process fabrication. This is a better way to illustrate the information obtained from Table 6. It provides the predicted optimal conditions for the process optimization. For Process 1, the optimal condition predicted is A_1, B_1, C_2 as for having higher WSNR values. Process 2 on the other hand is A_2, B_1, C_2 while Process 3 is A_1, B_1, C_2 and Process 4 is also A_1, B_1, C_2. An observation that can be seen is that Factor C (machine temperature) in Process 2 (calendaring) has the biggest margin with 0.2221 differences of its two levels. This tells us that such factor is quite sensitive if we change the level values thus it is a significant factor in producing a good quality of process or product. On the other hand, the

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
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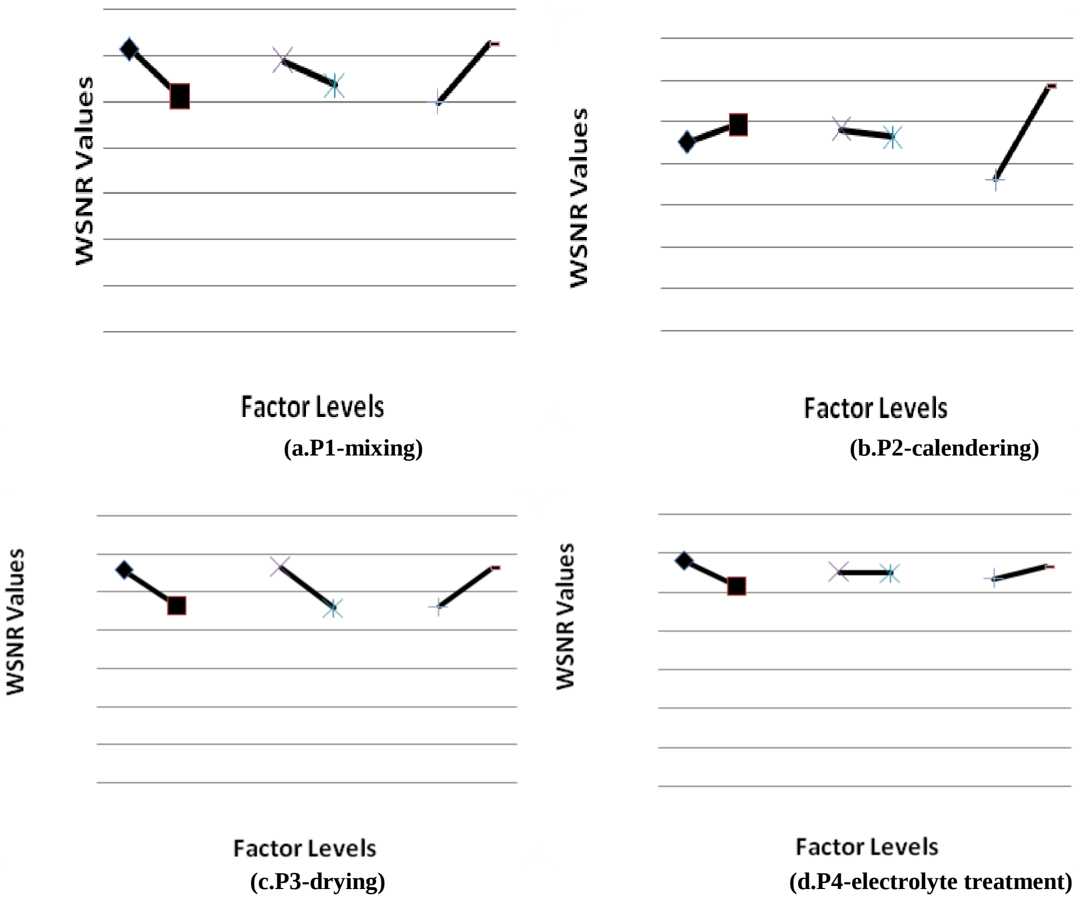
very small margin of 0.0011 obtained in Process 4 (electrolyte treatment) and Factor B (molarity) indicates that such factor does not have much effect on the outcome if we change the level values. In a later section, a more appropriate way for determining significant and insignificant factors using ANOVA will be discussed.

Table 6 .Main Effects On WSNR for Every Factor Investigated of the Respective Process

Process	Factors	Low Level, L1	High Level, L2	$WSNR_{max}$ - $WSNR_{min}$
1	A Mixing Speed	*0.6167*	0.5101	0.1066
Mixing	B Mixing Time	*0.5889*	0.5379	0.0509
	C Amount of AC	0.4990	*0.6278*	0.1288
2	A Calendaring time	0.4505	*0.4943*	0.0438
Calendaring	B Thickness	*0.4813*	0.4635	0.0178
	C Machine temp.	0.3614	*0.5835*	0.2221
3	A Heating time	*0.5575*	0.4641	0.0934
Drying	B Heating temp.	*0.5636*	0.4580	0.1057
	C Vacuum	0.4617	*0.5600*	0.0984
4	A Electrolyte name	*0.5801*	0.5195	0.0606
Electrolyte	B Electrolyte molarity	*0.5504*	0.5493	0.0011
Treatment	C Electrolyte amount	0.5340	*0.5656*	0.0315



(a.P1-mixing) (b.P2-calendering)

(c.P3-drying) (d.P4-electrolyte treatment)

Fig. 2 .Factor Effects On WSNR.

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V. CONFIRMATION EXPERIMENT

In confirmation of the predicted optimal settings obtained from the proposed Taguchi-GA approach, verification tests were conducted and another three samples were each produced and the results obtained are tabulated in Table 7. To evaluate the findings, a comparison of the standard deviation (SD) for all of the trials is conducted. The smaller value of SD implies the consistency of the samples and thus indicates that they are close to the target value. Consistency is related to process repeatability and robustness of product.

Table 7 .Experimental Output Data for Confirmation Experiments

Process	Sample 1	Sample 2	Sample 3
1 (A_1, B_1, C_2)	2.425 F; 1.602 Ω	2.388 F; 3.691 Ω	2.403 F; 2.925 Ω
2 (A_2, B_1, C_2)	2.051 F; 1.811 Ω	2.026 F; 2.008 Ω	2.095 F; 1.760 Ω
3 (A_1, B_1, C_2)	2.294 F; 2.571 Ω	2.310 F; 2.529 Ω	2.244 F; 2.708 Ω
4 (A_1, B_1, C_2)	2.199 F; 1.98 Ω	2.222 F; 1.85 Ω	2.213 F; 2.00 Ω

The standard deviations (SD) were obtained using the following formula;

$$SD = \sqrt{\frac{N\sum(x^2)-(\sum x)^2}{N\,(N-1)}} \qquad (14)$$

where N is the number of replication and X is the experimental data.

Table 8 .SD for Each Experiment and under Optimal Conditions

Process	Experiment, i	SD (cap)	SD (ESR)
1	1	0.0601	3.8223
	2	0.0751	5.1110
	3	0.1766	2.3861
	4	0.1111	4.3636
	5 (A_1, B_1, C_2)	0.0186	1.0568
2	1	0.0549	0.6171
	2	0.1090	0.5965
	3	0.0420	0.3996
	4	0.1445	0.4193
	5 (A_2, B_1, C_2)	0.0349	0.1310
3	1	0.0853	0.1893
	2	0.1847	0.3122
	3	0.1760	0.3279
	4	0.0738	0.1323
	5 (A_1, B_1, C_2)	0.0650	0.0936
4	1	0.1245	0.2566
	2	0.0738	0.1323
	3	0.0123	0.1094
	4	0.1524	0.1000
	5 (A_1, B_1, C_2)	0.0116	0.0814

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Table 8 shows that the predicted condition in every process yields a certain extent of improvement (reduction) of capacitance and ESR standard deviation of values. Such findings proved that the GA results have successfully optimized the weightings and has thus maximized the values of SN ratio for both responses The overall improvement percentage is determined as the ratio between sums of the improvement in values of all responses and the sum of the SNRs of initial responses for all responses [1]. The computations are presented in Table 9.

Table 9 .Initial, Predicted and Actual Improvement Of SN Ratios

Process	Responses	Initial condition (dB)	Predicted condition (GA) (dB)	Confirmation (dB)	Improvement (dB)
1	Capacitance	16.99	15.69	17.166	0.176
	ESR	-12.85	-21.22	-9.164	3.686
	Optimal setting	A_2, B_1, C_2*	A_1, B_2, C_2** *A_1, B_1, C_2******	A_1, B_1, C_2	
	Overall improvement in dB (%)				*12.9 %*
2	Capacitance	15.34	15.34	15.340	0.000
	ESR	-7.75	-7.75	-5.798	1.952
	Optimal setting	A_2, B_1, C_2*	A_2, B_1, C_2**	A_2, B_1, C_2	
	Overall improvement in dB (%)				*8.4 %*
3	Capacitance	17.11	17.63	17.18	0.07
	ESR	-8.43	-8.51	-8.31	0.12
	Optimal setting	A_1, B_1, C_1*	A_2, B_1, C_2** *A_1, B_1, C_2******	*A_1, B_1, C_2*	
	Overall improvement in dB (%)				*0.7 %*
4	Capacitance	16.34	17.52	16.44	0.10
	ESR	-7.61	-8.50	-5.78	1.83
	Optimal setting	A_2, B_2, C_1*	A_2, B_1, C_2** *A_1, B_1, C_2******	A_1, B_1, C_2	
	Overall improvement in dB (%)				*8.1 %*

* Combination obtained from OEC computation (0.7:0.3).
** The highest WSNR given from Table 4.
*** Predicted condition from GA which is not in the L_4 Orthogonal array.

The SNRs for the initial condition are obtained by assigning 0.7 weighting for the capacitance response and 0.3 for the ESR response arbitrarily, based on the consensus that the capacitance performance should dominate the ESR response before conducting the GA approach. The GA method then searches for the optimal weightings that maximize the SNR for both responses to improve the performance of process factors. Different Capacitance to ESR ratio combinations (total=1) have also been tested - 0.6:0.4, 0.2:0.8 etc. It was found that after the capacitance ratio being altered gradually for example 0.2, 0.3, 0.4 etc, the outcome results in the same experimental run (e.g. Run 2) as the best run for the respective process. However, until at a certain ratio (e.g 0.8:0.2) the results turn up to give a different experimental run (e.g. Run 3) as the best run. This shows that the weighting has certain impact on the optimal setting to be predicted. If that is so, there is a chance to fully optimise the SNR. This is can be done without using engineering judgment. For this case study, only one weighting ratio, 0.7:0.3, was used for the OEC computation. This is treated as the initial condition in which to compare WSNR results.

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Table 10 .OEC Values to Determine the Optimal Setting for the Initial Condition

Process	Experiment, i	Combination	OEC (0.7:0.3 weighting)
1	1	A_1, B_1, C_1	0.5125
	2	A_1, B_2, C_2	0.5756
	3	*A_2, B_1, C_2*	*0.5940*
	4	A_2, B_2, C_1	0.4669
2	1	A_1, B_1, C_1	0.3754
	2	A_1, B_2, C_2	0.5641
	3	*A_2, B_1, C_2*	*0.5941*
	4	A_2, B_2, C_1	0.3112
3	1	*A_1, B_1, C_1*	*5.8250*
	2	A_1, B_2, C_2	5.1260
	3	A_2, B_1, C_2	5.3430
	4	A_2, B_2, C_1	4.3260
4	1	A_1, B_1, C_1	0.5012
	2	A_1, B_2, C_2	0.2526
	3	A_2, B_1, C_2	0.4628
	4	*A_2, B_2, C_1*	*0.6149*

Table 10 presents how the combination of the initial condition is made by selecting the highest OEC values in every fabrication process. The SNRs of those experimental runs that based on the processing parameters as in Table 4 are compared with the SNRs of the confirmation experiments which use WSNR values. As in Table 9, it is observed that 12.9%, 8.4% and 8.1% improvement in dB was obtained for the mixing, calendaring and electrolyte treatment process respectively by using the proposed Taguchi-GA approach. These are quite impressive results. However, the drying process does not produce much improvement (0.7%). One possible reason for this small improvement is that the optimization has reached its certain limit for given factors and levels assigned. Unless different factors are added in to be investigated, this could be further improved.
The purpose of ANOVA in this study is to determine which of the process factors are significantly affect the performance characteristics [1] in the coin super capacitor fabrication. To achieve this, the total variability of the multi-objective WSNR measured by the sum of squared deviations is separated from the total mean of WSNR, before converting into percentage contribution for every individual factor. This part was implemented by utilizing the Qualitek-4 software. Some of the factors are pooled to avoid calling something significant when it is not. This is to maximize the percentage contribution of the dominant and significant factors. Table 11 displays the ANOVA results.

Table 11 .Results of ANOVA Analysis on WSNR

Process	Factor	DOF	Sum of Squares	% Contribution
1	A	1	0.011	37.181
	B	1	0.002	8.360
	C	1	0.016	54.130
	Error	0		
	Total	3	0.030	100 %
2	A	1	0.001	3.16
	B	(1)	(0)	POOLED
	C	1	0.049	96.00
	Error	1	-0.01	0.84
	Total	3	0.051	100 %

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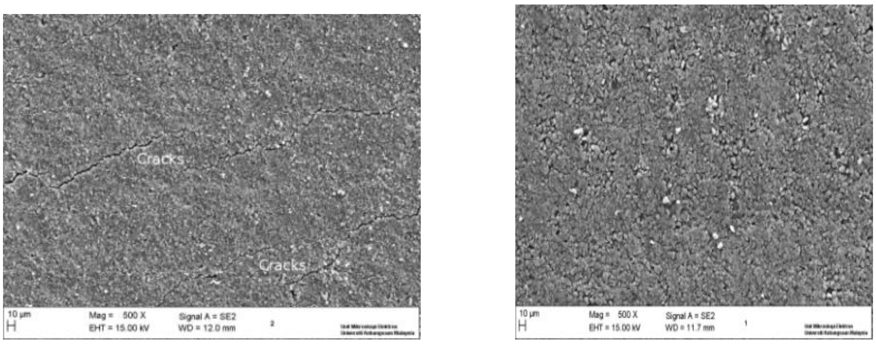
3	**A**	**1**	**0.008**	**29.230**
	B	**1**	**0.011**	**37.973**
	C	**1**	**0.009**	**32.458**
	Error	**0**		
	Total	**3**	**0.029**	**100 %**
4	**A**	**1**	**0.003**	**91.503**
	B	**(1)**	**(0)**	**POOLED**
	C	**1**	**0.001**	**24.803**
	Error	**1**	**-0.001**	**-16.306**
	Total	**3**	**0.004**	**100 %**

Consequently, optimal conditions for every process can be set as A_1, B_1, C_2 for the mixing process, A_2, B_1, C_2 for the calendaring process, A_1, B_1, C_2 for the drying process, and A_1, B_1, C_2 for the electrolyte process. It is found that the most significant process factor for the respective process is in the sequence of machine temperature (96%) in the calendaring process, followed by the KCl electrolyte (91.503%) in the electrolyte treatment process, the amount of activated carbon (54.13%) in the mixing process, and finally the heating temperature (37.97%) in the drying process. Such process factors with a high percentage contribution obtained statistically are believed to have a huge impact towards the performance of the supercapacitor fabricated.

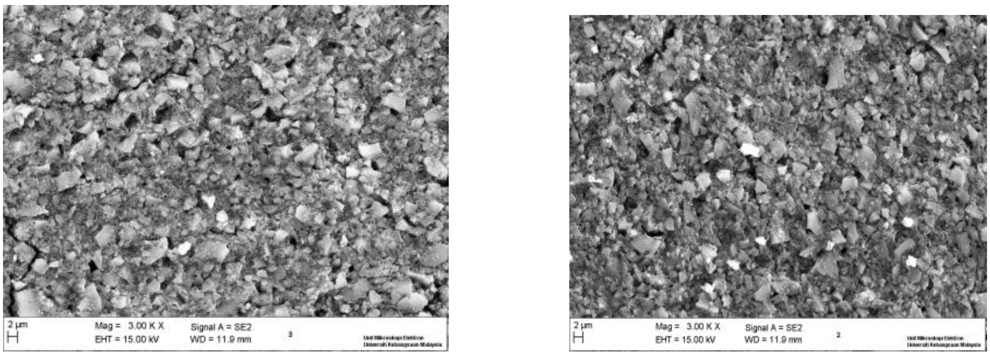
As part of this effort we also wanted to determine the physical effect of an "optimized" process factor on the material itself. Referring to the SEM pictures below, we observe a difference in the homogeneity and structure of the electrode material after adding the binder and the mixing process for different parameters i.e. before and after optimization.



(a) (b)

Fig. 3: Optimizing AC % A) Before Optimizing (Cracks), B) After Optimizing (Cracks Free).

Figure 3, shows the effect of optimizing AC and binder percentages on the cracks formed on the surface of the electrode.



(a) (b)

Fig. 4: Optimizing the Mixing Process A) Before B) After

ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
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Optimizing the mixing process can result in more homogenise structure, resulting in smaller gaps between the particles, which can improve the ESR and the capacitance of the supercapacitor.

VI. CONCLUSION

The super capacitor fabrication process dealing with a multi response problem has been presented in this paper. From the experimental and analytical results, the conclusions are as follows:

1. Taguchi method has successfully minimized the cost and time span of the experimental procedure consisting of three factors and two-level each. Only four trials are required when using the orthogonal array experiment.
2. The proposed integrated approach has improved the SNR (dB). Hence, optimal conditions have great influences on the design factors with less sensitivity to the noise factors.
3. The proposed Taguchi-GA integrated strategy provides a robust design in the sense of reproducibility and reliability. This could not be achieved by the OEC approach alone as this approach is dependent on engineering judgment (that has higher variation), a mean value that is far from the desired target value if those judgments were inaccurately made.

ACKNOWLEDGMENT

The authors would like to acknowledge funding support under Sahz Holdings Sdn. Bhd.

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