Air Bubble Reduction in Epoxy Resin Casting Process for CNC Industries

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***Abstract*—This paper presents a framework of Metaheuristic evolutionary elements on Taguchi array based on Particle Swarm Optimisation (PSO) Algorithm, encompassing all major algorithmic sequences which include evolution, concept, design steps, vital considerations, analysis and its industrial application. In our approach we trace the evolution of Taguchi method with the original orthogonal array to identify the influential effects of main and some selected interaction of parameters. The evolutionary elements are then determined from PSO Algorithm and merged to generate the new array without performing the orthogonal array at the best so far design point. This concept contributes its present procedure, thereby stating the significance of this proposed method over other conventional techniques. The method is applied to reduce air bubbles formed during an epoxy casting process in the production of linear motors, commonly used in CNC, to reduce rework and unacceptable resistance value. The number of air bubbles per united area is reduced from 0.065 from the current operating condition to 0.009 with the optimal setting obtained from the proposed method. Furthermore the process variation is also significantly reduced. It thus reinforces the vitality of this proposed method as an efficient tool of robust design followed the conventional one.**

***Index Terms*—CNC, epoxy resin casting process, metaheuristic, particle swarm optimisation, Taguchi method, signal to noise ratio**

I. Introduction

The epoxy resin casting process is one of the most promising technology available today. This process is capable of making large complex three-dimensional part with high physical performance and high surface finish. If there are imperfections of the parts, this brings the damage quickly to the whole linear motor [1]. The most common damages to the parts are the air bubbles on the surface, color thickness, resistance and so on. Many researchers have carried out experimental investigations to study the effects of process parameters on the most important quality characteristic of the number of air bubbles per united area. In order to analyse the number of air bubbles in linear motors, Taguchi design and analysis were employed in the context of response surface methodology (RSM).

Design optimisation has become increasingly important in industrial applications. On Taguchi method, excessive variation in performance was the root cause of poor quality characteristics. These were then counterproductive to the society at large. Taguchi focused on the importance of reducing process variability around a specified level of the target. This brings the process mean on target and insensitive to various sources of noise called Robust Parameter Design [2]. Instead of using the conventional designs such as factorial designs, Taguchi addresses the orthogonal arrays by careful selecting design parameters. In order to achieve the most influential parameters to the process Taguchi proposed an effective and an efficient method to determine the feasible combination of design parameters that reduces variability in product responses. It is called as signal to noise ratio [3].

However, under higher levels of noisy environment and economical design the repetition of orthogonal array is quite impractical. Metaheuristic evolutionary elements are proposed on the original array. Metaheuristic algorithms adapt natural phenomena in computers to address problems that were previously complex or impossible to solve. Among these metaheuristics, some are population based and single solution based. Genetic Algorithm (GA) [4], Particle Swarm Optimisation (PSO) [5], Ant Colony Optimisation (ACO) [6], Firefly (FA) [7], Krill Herd (KHA) [8, 9] and Elevator Kinematic Optimisation (EKO) [10] are considered population-based. Simulated Annealing (SA) [11, 12] and Tabu Search (TS) [13] are single solution-based. Usually the optimal solution from this kind of methods sometimes cannot be guaranteed. Therefore, this study presents a

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novel approach or Metaheuristic evolutionary elements on Taguchi array based on Particle Swarm Optimisation Algorithm. It can be easily implemented to overcome several deficiencies in conventional Taguchi methods and to create ever the better results with simple algorithmic tools.

The main objective of this work was to select optimum process parameter levels for an epoxy resin casting process. The experiments were designed using Taguchi L8 orthogonal array. An analytical model was developed for optimising the process parameters. Preheat temperature, vacuum time, mixing time, and oven temperature were the process parameters considered in this study. In order to overcome the difficulties associated with the Taguchi method, we propose a particle swarm optimisation algorithm for finding the alternative solutions for the traditional orthogonal arrays. The major advantage of the proposed method is that it does not require any new series of the experimental designs if there is no main or interaction effects between parameters. The proposed method approach does not set any specific assumptions on the behavior or the preference structure of the design maker. It means that the proposed method will still work and provide various alternatives whether or not the design maker has enough time and capabilities for co-operation. In the second section, the epoxy resin casting process (ERCP) is briefly described. The fundamental PSO algorithm is included in section "Metaheuristic evolutionary elements on Taguchi array (MEETA)." In section "Numerical results and analysis" results obtained by the MEETA are presented. Finally, the conclusions and discussions of the research and the suggestions for further studies are given in section "Conclusions and discussions."

II. Epoxy Resin Casting Proces (ERCP)

CNC machines can produce workpieces quickly, accurately and precisely. It has high accuracy because CNC machines are used in linear motor technology. This research is to study and determine preferable levels of parameters affecting the process response or the number of air bubbles in an epoxy resin casting process when producing a part of linear motors. Linear motor is a drive system without the need for a transmission system such as sprockets, gears or belts (Fig. 1). This makes automatic machinery using linear motors have the following advantages of ability to produce higher quality parts, higher throughput, and lower maintenance capacity [14].

Figure 1. Linear motor and its air bubble formation on the surface area

Thermoset epoxy resin is a widely used. Since epoxy resin is an inert material, it has good adhesion properties can be easily formed. Therefore, it is suitable to use on the surface to prevent scratching, protects against acid, alkali and chemicals including various decorative coatings. It is used to coat the car body, tools, important tools and to cover the wires. In electrical and electronic applications, epoxy resin has benefit on the resistance of the dielectric or dielectric strength because of its little shrinkage, good holding strength. It also withstands on various environments such as waterproof and moisture resistant. It is used for high voltage insulators to make switchgears and to insulate transients. In addition, epoxy resins are reinforced via fibers and laminates.

To enhance the strength and life time of epoxy part, air bubbles formed during ERCP have been eliminated. They are results of air rushing to the mixture of the resin and the hardener during the mixing. In general, the process with longer mixing times with a combination of vacuum time are preferable because they allow the mixture to be combined slowly, carefully and thoroughly without injecting any air. Proper preparation of preheat and oven temperature is one of the most important steps to minimise the air bubble formation. The experienced worker should be also considered as an uncontrollable parameter or noise (Fig. 2).

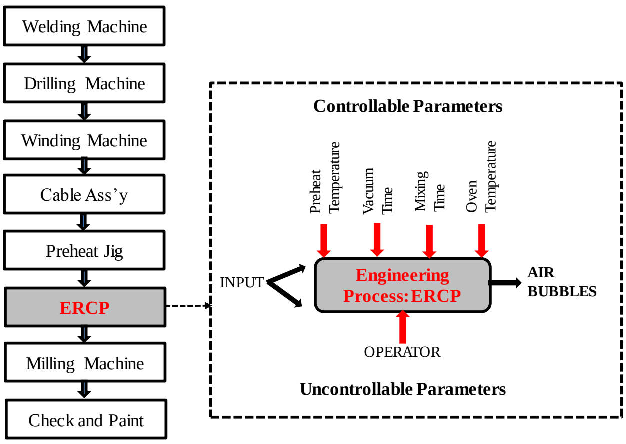

Figure 2. Design and noise parameters of the ERCP

III. Metaheuristic Evolutionary Elements on Taguchi Array (MEETA)

A. *Taguchi Design and Anlysis*

There are two main phases of first and second order experiments for response surface optimisation after the screening experiment (Luangpaiboon, 2019 [15]). Taguchi design and analysis is normally performed in the first phase. Taguchi introduced an experimental design or an orthogonal array denoted by OA. OA is a matrix whose columns have the property that in every pair of columns each of the possible ordered pairs of elements appears the same number of times. The symbols used for the elements of an orthogonal array are arbitrary. Mainly, papers use the symbols (0, 1, 2) or (-1, 0, +1) to denote the parameter levels of (Low, Medium, High), respectively. Orthogonal arrays can be viewed as plans of multi-parameter experiment where the columns correspond to the parameters, the entries in the columns correspond to the test levels of the parameters and the rows correspond to the test runs. Key performance measures via Taguchi design consist of an analysis of mean via the actual yields and signal to noise ratio.

An analysis of Mean (ANOM) is the response mean for each combination of control parameters levels in a Taguchi design. The aim of this method is to identify which parameter effects more on parameters and remaining selected interaction effects giving an indication of the performance trend over the ranges of main or interaction of parameters [16]. The delta is used to identify the size of those effects by the taking the difference between the highest and the lowest value of average for a parameter and the rank in the response. The main parameter or interaction effects with the highest delta level is assigned rank 1, the parameter with the second highest delta is assigned rank 2 and so on. In the case that the outer array design for noise parameters was used, the output response is analysed using SN ratio for the specific quality characteristics. The SN consolidates multiple data points into a single value reflecting the amount of variance present for the specific quality characteristic selected. In this study, an objective is to minimise the response (y) given by the following function.

$$SNS = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)$$

B. Particle Swarm Optimisation

Particle swarm optimisation method (PSO) was first suggested by Kennedy and Eberhart in 1995 [17]. It has been used as the very promising optimisation technique for solving various global optimisation problems. Its algorithmic procedures are inspired by the social and cooperative behavior of various species like birds or fish. The PSO algorithm starts from a population or swarm of potential design points called particles [18, 19]. These particles move through the search space or feasible region of operations. Each particle has its specified velocity while searching for the optimum. Each particle keeps the track of its previous best position as personal best or global best via a memory [20, 21]. The sequential procedures of the PSO may be described below.

Step 1: Determine the position of the ith particle represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ in a D-dimensional search space.
Step 2: Maintain a memory of the ith particle with its previous best position or $P_{best,i} = (p_{i1}, p_{i2}, \ldots, p_{iD})$.
Step 3: Determine the best one among all the particles in the population represented as $P_{gbest,i} = (p_{g1}, p_{g2}, \ldots, p_{gD})$.
Step 4: Assign the velocity of each particle represented as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$.
Step 5: Combine the P vector of the particle with the best fitness in the local neighborhood, designated g, and the P vector of the current particle to adjust the velocity along each dimension in each iteration.
Step 6: Determine a new position of the particle using the new velocity (Δ) as shown in the two basic equations below:

$$\Delta = \omega V_i + c_1 r_1 (P_{best,i} - X_i) + c_2 r_2 (P_{gbest,i} - X_i)$$

$$\text{New } X_i = X_i + \Delta$$

where Δ is the inertia to the previous velocity, $-V_{max} \le V_i \le V_{max}$; c_1, c_2 are acceleration constants determining a local learning factor and a global learning factor, respectively. Two parameters of r_1 and r_2 are the uniformly generated random numbers in the range of [0,1]; V_{max} is a maximal velocity of the particle [22].

C. Metaheuristic Evolutionary Elements on Taguchi Array (MEETA)

Metaheuristic evolutionary elements on Taguchi array (MEETA) is then proposed to find optimal levels of k influential parameters leading to the lowest level of the process response. Moreover, lower and upper levels of process parameters can be included in order to avoid design points that extrapolate too far outside the feasible region of the experimental design spaces. In order to achieve the evolutionary elements from metaheuristics, in this case the PSO, a conventional orthogonal array is used to determine the estimated influential process parameters with or without noise parameters. PSO Evolutionary elements are then applied with a consideration of the feasible ranges in terms of lower (LB) and upper (UB) levels of process parameters.

Taguchi designs or arrays of fractional factorial nature of two-or three-level arrays follows from the way these fundamental arrays are constructed on the first phase. The design points are then used to perform and measure their response. Taguchi analysis via the analysis of mean (ANOM) or the mean difference of the signal to noise ratio are performed to determine the most influential parameter without or with the noise parameters [23]. The second best design points are then applied the evolutionary elements from the PSO for constructing the new arrays, then illustrates their fractional factorial nature (Fig. 3). The orthogonal property might be impractical when the evolutionary elements are applied to overcome the noisy environment.

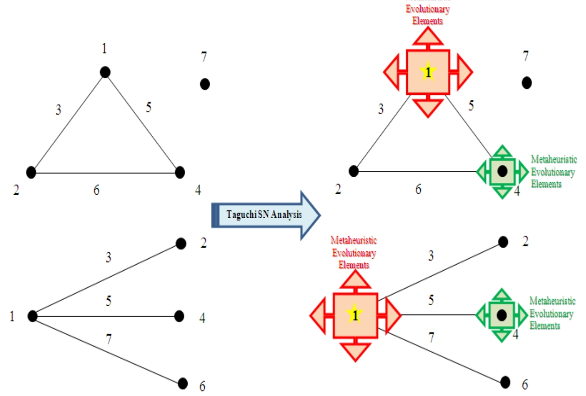

Figure 3. MEETA diagram for process improvement via L8 Taguchi design

IV. Numerical Results and Analysis

This research focuses on Bisphenol A (BPA) epoxy resin which is widely used as a component in the production of polycarbonate epoxy resin and other products. The range of BPA epoxy resin products includes circuit boards, composites, paints, adhesives and coatings. The epoxy resin casting process (ERCP) starts from a preparation of prototypes by setting a parting line to separate the mold on both sides. Later, they are assembled into the prepared container for forming. Epoxy materials are then mixed according to the desired ratio. Vacuum cabinet is used to decrease the air bubbles of the mixed resin as possible. After that, the mixture is poured into the prepared specimen and allowed to harden at a room temperature. Reversing is done to form the other side of the mold. When unpacking the container, the two sides of the mold are still attached. The workpiece is dehumidified so that the mold can be separated easily. The mold is then separated to check the resulting mold surface (Fig. 4).

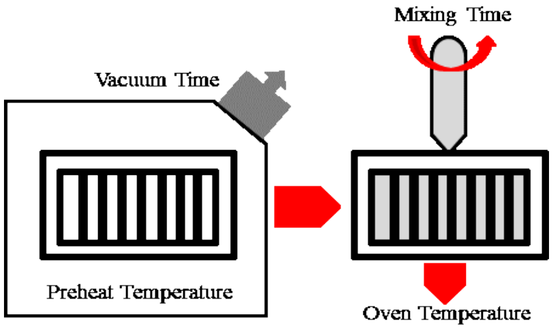

Figure 4. Epoxy resin casting process for linear motor

In this study, the numerical results of Metaheuristic evolutionary elements on Taguchi array are introduced in details. The ERCP has only one response of the number of air bubbles per unit area (Y). The parameter levels are controlled within their feasible ranges via explicit constraints. PSO metaheuristic is used to determine alternatives of conventional orthogonal array to form Taguchi response. The establishment of the MEETA is based on four influential parameters. Metaheuristic algorithm of the PSO optimised levels of the four influential parameters $(x_i, i = 1,2,3,4)$. These parameters consist of preheat temperature (x_1), vacuum time (x_2), mixing time (x_3) and oven temperature (x_4) as shown in Table I. The most common use of the completely randomised design via an analysis of variance is to screen all process parameters from all existing design points.

TABLE I. PARAMETERS AND THEIR CURRENT AND FEASIBLE LEVELS PROCESS AND NOISE PARAMETERS

Process Parameter	Level		Unit
	1	2	
Preheat Temperature	65-80	70	℃
Vacuum Time	10-25	15	Minutes
Mixing Time	5-10	7	Minutes
Oven Temperature	115-125	120 ℃	℃

On the screening experiments, a hypothesis test called analysis of variance (ANOVA) was used to determine if there are any significant differences between any of the ERCP parameter levels (Fig. 5). Here, ANOVA indicates that there is a significant difference for parameters of preheat temperature, vacuum time and mixing time since the observed levels of the variance ratio is statistically significant at 10% level of significance (Table II). However, based on the residual analysis to accurate the ANOVA, the residuals did not obviously meet the requirements for a parametric test, at least for the residuals versus fitted value to detect unequal error (Fig. 6).

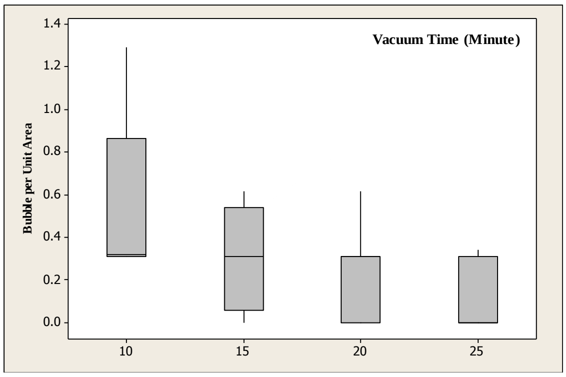

Figure 5. Box-Whisker plot for number of air bubbles per unit on the screening experiments

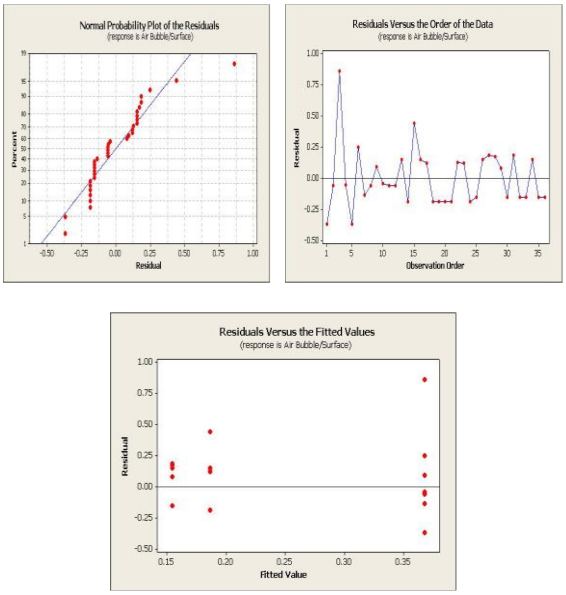

Figure 6. Residual analysis for ANOVA of the mixing time

Kruskal-Wallis test was appropriate to determine if the differences between the treatments are so statistically significant that they are unlikely to have occurred by chance. The likelihood of obtaining levels of H statistic as large as the ANOVA, were somewhere between 0.05 and 0.10 in forms of P-values. From both test it could be concluded that there are differences of some kind between our three process parameters. These influential parameters and their interaction effects of x_1x_2, x_1x_3 and x_2x_3 including an additional noise parameter of an operator with the 2-year experience are included to form Taguchi orthogonal Inner and outer arrays, respectively (Table III).

TABLE II. PROCESS PARAMETERS AND THEIR STATISTICAL SIGNIFICANCE VIA CRD-ANOVA AND K-W

Process Parameter	Level	Level	
		1	**2**
x_1	65 70 75 80	-	0.009
x_2	10 15 20 25	0.001	0.001
x_3	5 7 10	0.080	0.055
x_4	115 120 125	0.183	0.230

TABLE III. INFLUENTIAL PROCESS AND NOISE PARAMETERS INCLUDING THEIR TAGUCHI DESIGNED LEVELS

Process Parameter	Level		Unit
	1	**2**	
Preheat Temperature	70	80	°C
Vacuum Time	15	25	Minute
Mixing Time	7	10	Minute
Oven Temperature	115	120	°C

Noise Parameter	Level		Unit
	1	**2**	
Operator (N)	<2	>2	Years

Taguchi orthogonal arrays were employed in these industrial experiments to study four ERCP parameters with their three selected 2-parameter interactions and one noise parameter. Orthogonal arrays are highly fractionated factorial designs with the nature of confounding and additional assumptions about the physical industrial process. This experiment has four parameters at two different settings. A full factorial experiment would require 2^4 or 16 experimental runs. This case conducted a Taguchi experiment with an $L_8(2^7)$ orthogonal array (8 tests, 4 parameters, 2 levels) with two levels of one noise parameter. The experiment design is shown in Table IV.

TABLE IV. INFLUENTIAL PROCESS AND NOISE PARAMETERS INCLUDING THEIR TAGUCHI DESIGNED LEVELS PROCESS

Treatment	**Inner Array**							**Outer Array**	
	x_1	x_2	x_1x	x_3	x_1	x_2	x_4	**N1**	**N2**
1	1	1	1	1	1	1	1	0.322	0.318
2	1	1	1	2	2	2	2	0.311	0.295
3	1	2	2	1	1	2	2	0.252	0.269
4	1	2	2	2	2	1	1	0.241	0.227
5	2	1	2	1	2	1	2	0.240	0.241
6	2	1	2	2	1	2	1	0.230	0.222
7	2	2	1	1	2	2	1	0.170	0.174
8	2	2	1	2	1	1	2	0.159	0.169

The Taguchi arrays employed in this work were a selected fraction of 2-level-four-factorial designs with 8 treatments. The coded and corresponding actual parameter levels under two levels of noise are shown in Table IV. The matrix for the four parameters was varied at two levels of (1 and 2) for the 2-level factorial designs. Each design point or treatment was experimented in random order to avoid systematic error. The following equation can be applied to transform a real value (X_i^{ACTUAL}) into a coded value (X_i) according to a determinate experimental design:

$$X_i = \omega_i \left(\frac{X_i^{ACTUAL} - X_{i0}^{ACTUAL}}{\Delta X_i^{ACTUAL}} \right)$$

where ΔX_i^{ACTUAL} is the interval between the actual value in the centred point and the real value in the superior or inferior level of a parameter, ω_i is the major coded limit value in the matrix for the i-th parameter, and X_{i0}^{ACTUAL} is the real value in the centred point.

Taguchi signal to noise ratio (SN) is used as measurable level instead of standard deviation. Practically, the standard deviation cannot be minimised first and the mean brought to the target. The target mean level may change during the process improvement. This simultaneously brings both the improvement of quality through variability reduction and the improvement of measurement. This problem applied the SN ratio Smaller the Better (SNS) characteristic. The mean differences ($Delta$) in SNS were ranked as shown in Table V.

TABLE V. DIFFERENCES IN MEANS OF TAGUCHI'S SNS

Treatment	1	2	$Delta$	Rank
x_1	11.14	14.07	2.93	1
x_2	11.39	13.82	2.43	2
x_1x_2	12.81	12.4	0.42	4
x_3	12.31	12.9	0.59	3
x_1x_3	12.55	12.66	0.11	6
x_2x_3	12.65	12.56	0.08	7
x_4	12.68	12.53	0.15	5

MEETA showed the best performance in terms of the mean difference value. The highest rank is the preheat temperature. The PSO uses the two basic equations to generate the new level of the Taguchi array from strong members considered (Table VI).

TABLE VI. PARAMETER LEVELS VIA MEETA ON THE SECOND PHASE EXPERIMENTAL DESIGN

Treatment	**Inner Array**						
	x_1	x_2	x_1x_2	x_3	x_1x	x_2x_3	x_4
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2→ Δ	1	2→ Δ	1	2	1	2
6	2→ Δ	1	2→ Δ	2	1	2	1
7	2→ Δ	2	1	1	2	2	1
8	2→ Δ	2	1	2	1	1	2

The analysis of means (ANOM) is carried out for the selected more preferable parameter levels to determine the optimal levels of the process response or the number of bubbles per united area. The results of ANOM are represented in response graphs based on main and interaction effects (Fig. 7). The level of a parameter with highest value of SN ratio is the best combination level. In order to investigate the effects of ERCP parameters quantitatively the Box-Whisker plot is performed in three phases of the current, Taguchi design and analysis and MEETA.

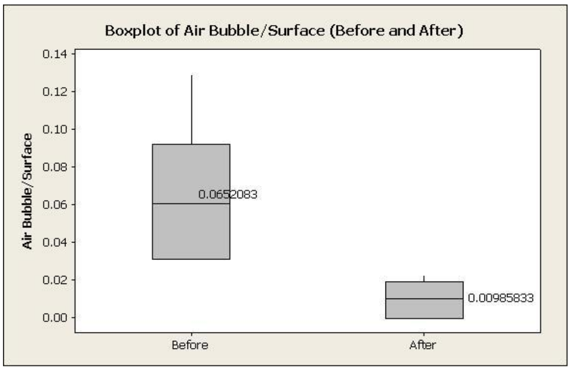

Figure 7. Air bubble before and after applying the MEETA

From MEETA optimisation results, it is found that the optimal values of preheat temperature, vacuum time, mixing time and oven temperature are at 80, 25, 5 and 115, respectively (Table VII). Further, it is also observed that the number of air bubbles per united area decrease from 0.0065 to 0.009.

TABLE VII. CURRENT AND THE NEW SETTINGS OF INFLUENTIAL PROCESS PARAMETERS

Process Parameter	Level		Unit
	Current	New	
Preheat Temperature	70	80	°C
Vacuum Time	15	25	Minute
Mixing Time	7	5	Minute
Oven Temperature	120	115	°C

IV. CONCLUSIONS AND DISCUSSIONS

The Taguchi design and analysis has been increasingly used in parameter designs. Apart from more conventional Taguchi implementation, there has been a significant amount of research efforts addressing the Taguchi limitations to make it more suitable for the use in noisy environment optimisations. Many techniques, especially metaheuristics, have been developed to facilitate this process optimisation embedded on Taguchi design. This study proposed the algorithmic procedures of the MEETA to determine the proper parameter levels of molding resin process i.e. Preheat Temperature, Vacuum Time, Mixing Time and Oven Temperature at $80^oC, 25\ s, 5\ s$ and 115^oC, respectively. The number of air bubble per united area was reduced from 0.065 in previous setting to 0.009 with the optimal parameter setting with significant variation reduction.

Although extensive research on design optimisations can be found in literature, there is still ample scope for further development work based on Taguchi array. There are also no attempts in literature to use the elementary elements from other metaheuristics embedded on Taguchi design and analysis framework. Future work in this direction should be encouraged.

CONFLICT OF INTEREST

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

AUTHOR CONTRIBUTIONS

P. LUANGPAIBOON contributed to the design, conceptualisation, methodology, software, validation, visualisation of the research, to the analysis of the results and to the writing - review & editing of the manuscript. S. JUTTIJUDATA contributed to an implementation, formal analysis, investigation, data curation of the research, and to the writing - review & editing of the manuscript.

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