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Review Article

Practical Applications of Taguchi Method for Optimization of Processing Parameters for Plastic Injection Moulding: A Retrospective Review

Ng Chin Fei,[1] Nik Mizamzul Mehat,[2] and Shahrul Kamaruddin[1]

[1] *School of Mechanical Engineering, Universiti Sains Malaysia, Engineering Campus, 14300 Nibong Tebal, Penang, Malaysia*
[2] *Department of Mould Technology, Kolej Kemahiran Tinggi MARA, Balik Pulau, Genting, 11000 Balik Pulau, Penang, Malaysia*

Correspondence should be addressed to Nik Mizamzul Mehat; nik_miza78@yahoo.com

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Determining the optimal processing parameter is routinely performed in the plastic injection moulding industry as it has a direct and dramatic influence on product quality and costs. In this volatile and fiercely competitive market, traditional trial-and-error is no longer sufficient to meet the challenges of globalization. This paper aims to review the research of the practical use of Taguchi method in the optimization of processing parameters for injection moulding. Taguchi method has been employed with great success in experimental designs for problems with multiple parameters due to its practicality and robustness. However, it is realized that there is no single technique that appears to be superior in solving different kinds of problem. Improvements are to be expected by integrating the practical use of the Taguchi method into other optimization approaches to enhance the efficiency of the optimization process. The review will shed light on the standalone Taguchi method and integration of Taguchi method with various approaches including numerical simulation, grey relational analysis (GRA), principal component analysis (PCA), artificial neural network (ANN), and genetic algorithm (GA). All the features, advantages, and connection of the Taguchi-based optimization approaches are discussed.

1. Introduction

Injection moulding has the highest efficiency, largest yield, and highest dimensional accuracy among all the processing methods. More than 1/3 of all thermoplastic materials are injection moulded and more than half of all polymer processing equipments are for injection moulding [1]. Nowadays, injection moulding bears the responsibility of mass-producing plastic components to meet the rapidly rising market demand as a multitude of different types of consumer products including medical, electronics, and automobile products are made of injection-moulded plastic parts [2]. Moreover, the final products, which exhibit good dimensional accuracy and excellent surface finish, have further proven the value of injection moulding process. However, as with any process, there are also some drawbacks associated with plastic injection moulding. Typically, injection moulding process is a cyclic process which consists of four significant phases: filling, cooling, packing, and ejection [3]. Hence, the complexity of injection moulding process creates a very intense effort to keep the quality characteristics under control.

Product quality is the concern of the manufacturers and customers while high product quality consistency and high production rate is the key to the industry's success. As noted by [4], there are many factors contributing to the occurrence of defects that affect the quality of injection-moulded parts during the production. During injection moulding process, the material selection, part and mould designs, and the processing parameters interact to determine the quality of plastic product [5]. Inappropriate combination of material selection, part and mould design, and the processing parameters can cause numerous production problems (e.g., product defects, long lead time, much scrap, high production costs, etc.), reduce the competitive price advantage, and decrease the company's profitability. By identifying the root cause of

the defects, it will contribute not only to the elimination of the part defects but also indirectly lead to the quality improvement of the moulded parts.

The complexity of injection moulding has increased the difficulty to maintain the process under control. There are enormous processing parameters to be controlled during injection moulding as illustrated in an Ishikawa cause-effect diagram (Figure 1). Generally, the processing parameters involved in injection moulding can be grouped into four basic categories: temperature, pressure, time, and distance [6].

2. Optimization of Injection Moulding Processing Parameters

Many studies were carried out to investigate the influence of the injection moulding parameters on the mechanical properties of moulded parts and the occurrence of moulding defects [7–9]. Reference [10] employed five process parameters (injection speed, melt temperature, mould temperature, metering size, and hold pressure time) to discuss the effects of process parameters on the micromoulding process and part quality of micro gears. Reference [11] employed six process parameters (mould temperature, melt temperature, gate dimension, packing pressure, packing time, and injection time) to determine the optimal processing parameter settings to reduce warpage of an injection-moulded plastic part with a thin shell feature. Reference [12] proposed eight control process factors (open mould time, mould temperature, melt temperature, filling time, filling pressure, packing time, packing pressure, and cooling time) to determine the optimal process parameter settings for a cell phone shell part with a thin shell feature with considerations of multiple quality characteristics, including strength, shrinkage, and warpage.

It was found that there is a strict correlation between processing parameters and the quality of the injection-moulded parts where an optimal combination of processing parameters can lead to significant improvement of the part quality. Reference [13] optimized the process conditions including mould temperature, melt temperature, injection time and injection pressure to establish a soft computing model with minimum shear stress. The result showed that the maximum shear stress has a significant reduction of 24.9% after the optimization of process conditions. Reference [14] reduced the warpage of an injection-moulded bus ceiling lamp base by 46.5% with the optimum values of processing parameters, including the mould temperature, melt temperature, packing pressure, packing pressure time, and cooling time. Another study with similar aim, which was conducted by [15], also indicated that the optimal combination of processing parameters managed to reduce the warpage of the initial thin shell plastic model significantly by 51%. In another study, [16] investigated the influence of processing parameters on shrinkage and warpage of a cellular phone casing. It was found that packing pressure is the most important parameter compared to other studied factors such as mould temperature, melt temperature, and injection speed. When the packing pressure was increased, the shrinkage and warpage were reduced drastically. In contrast, improper setting of processing parameters may induce devastating defects on the products, such as warpage, shrinkage, sink mark, and residual stress [17]. Therefore, determining the optimal processing parameters is performed routinely in the plastic injection moulding industry as it has a direct and dramatic influence on product quality and costs.

Previously, the setting of the injection moulding process parameters involves a trial-and-error method [13]. However, it is difficult to obtain an optimal parameter setting for complex manufacturing processes because trial-and-error method is "one change at a time" testing [18]. This tuning exercise is repeated until the quality of the moulded parts is found satisfactory, thus incurring high production cost as well as long setup time [19]. Moreover, the adjustments and modifications of processing parameters rely heavily on the experience and intuition of the moulding personnel [20]. Nevertheless, the growing demand in industry for expert moulding personnel far exceeds the supply and it needs more than 10 years' experiences for an amateur moulding personnel to become an expert [21]. Due to the shortage of the experienced moulding personnel, the traditional trial-and-error method is no longer good enough in determining the parameter setting of injection moulding. Many researchers have attempted various approaches in the determination of process parameters for injection moulding in order to obtain consistent quality of moulded parts.

The purpose of this research is to present an array of literature related to the broad use of Taguchi method in the determination of process parameters for plastic injection moulding. The review will shed light on the application of Taguchi method that, if taken into considerations, is expected to improve the effectiveness of the optimization by incorporating with other techniques. Prior studies are organized into two categories, namely, standalone Taguchi method and integration of Taguchi method with various approaches including numerical simulation, grey relational analysis (GRA), principal component analysis (PCA), artificial neural network (ANN), and genetic algorithm (GA). The features, advantages, and connection of these approaches are reviewed in this research.

3. Standalone Taguchi Method

Starting in the early 1920s, Sir R. A. Fisher introduced the Design of Experiments (DOE) method in ancient agricultural sciences as to determine the optimum treatments or trial conditions in order to produce the best crop [22]. Fisher's first idea was to lay out all combination of the involved factors in the experimental study and varied all the factors simultaneously in a full factorial design. The aim of experimental design is to study the effects of interaction between the variables which have largely been ignored in the trial-and-error method. The traditional DOE is a statistical approach to investigation of a system or process in which it allows a judgement on the significance of input variables to the output, either on their own influences, the interactions between the inputs, or not at all. Researches which were done on the optimization of injection moulding conditions via traditional

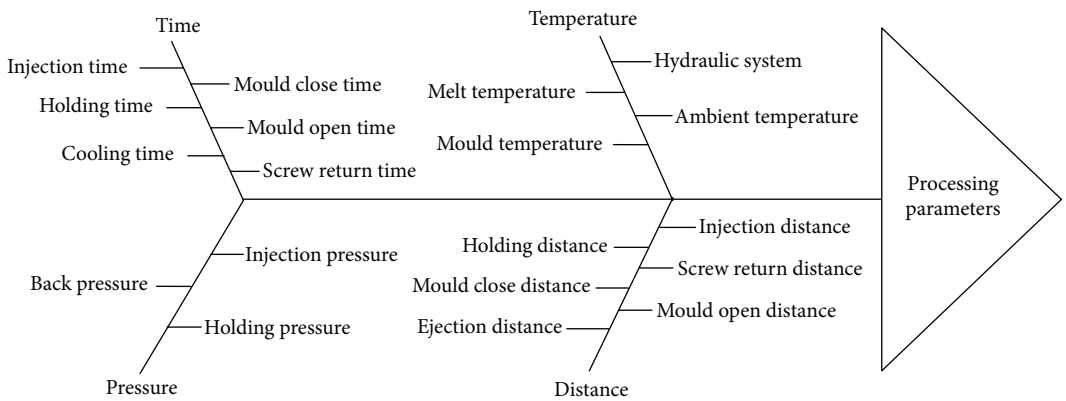

Figure 1: Ishikawa diagram of processing parameters in injection moulding.

DOE method can be divided into full factorial design and fractional factorial design [23].

A full fractional design will identify all the possible combinations for a given set of factors. In view of the fact that most industrial experiments usually demand a significant number of factors, a full factorial design results in performing a large number of experiments. However, it is very costly and time-consuming [24]. Therefore, fractional factorial design is proposed by selecting a limited number of experiments from all the possibilities that generate the most information in order to reduce the number of experiments to a practical level. Although fractional factorial design is well known, it is too complex and there are no general guidelines for its application or the analysis of the results obtained by performing the experiments [25].

Considering these difficulties, Dr. Genichi Taguchi has developed a new experimental strategy, Taguchi method which utilizes a modified and standardized form of DOE in the late 1940s [26, 27]. The application of Taguchi method has attracted more attention in the literature for the past 20 years and nowadays the Taguchi method has been widely applied to various fields, such as manufacturing system [28], mechanical component design [29], and process optimization [30, 31]. The popularity of Taguchi method is due to its practicality in designing high quality systems that provide much-reduced variance for experiments with an optimum setting of process control parameters.

Standalone Taguchi method is adopting the Taguchi's elements single-handedly from the experimental designing stage to the final optimization process. The parameter design of the Taguchi method utilizes orthogonal array (OA), signal-to-noise (S/N) ratios, main effects, and analysis of variance (ANOVA). OA provides a set of well-balanced (minimum experimental runs) experiments and Taguchi's S/N, which are logarithmic functions of desired output, serve as objective functions for optimization [32]. The main effects and ANOVA are carried out after performing the statistical analysis of S/N ratio. The main effects analysis is used to determine the optimal combination of processing parameters at the specific level with highest mean response whereas ANOVA is employed to estimate the error variance and determine the significance of the selected parameters. The aforementioned techniques help in simplifying experimental design, data analysis, and prediction of optimum results. As a result, Taguchi method is considered to be an important approach to minimize performance variation and hence, the interest in the literature of Taguchi method continues to grow.

Reference [33] employed the Taguchi method to optimize seven processing parameters, including melt temperature, mould temperature, injection speed, injection pressure, short-shot size, gas injection pressure, and gas injection delay time, to improve surface roughness in gas assisted injection moulding. The results showed that the process control becomes more critical and difficult with new gas-related processing parameters such as the amount of melt injection, gas pressure, and gas injection delay time. Nevertheless, the optimal parameters setting has successfully improved the surface roughness to 6.89 and melt temperature was found to be the most significant factor affecting surface roughness followed by gas injection delay time. Reference [34] conducted experiments adopting a L_9 orthogonal array to optimize the processing parameters of ABS mouldings produced from two different mould materials including steel and aluminium. In this study, multiple quality characteristics such as elasticity module, tensile strength at yield, tensile strain at yield, tensile strain at break, flexural modules, and Izod impact strength were analyzed individually via the main effects for both mould materials. Therefore, the results generated one optimal combination of processing parameters with the highest S/N values for different performance measure, indicating that the multiresponse optimization was ineffective as it is impractical to obtain so many optimal parameters setting to improve multiple quality characteristics simultaneously.

Reference [35] also exploited the L_9 experimental design to study the effect of processing parameters on the weld-line of the right door of copy machine which was modelled with three gates. Four processing parameters including melt temperature, injection speed, and injection pressure were optimized to eliminate the weld-line on the plastic part. Based on the experimental data at optimal level combination, the weld-line defect has significantly reduced through the optimization and it was found that the melt temperature

was the most important parameter affecting the visibility of weld-line. In another study, [36] further improved the weld-line strength of an injection-moulded part by utilizing the Taguchi optimization method. The study was carried out on a special-designed mould wherein the specimens which are having different cross-sections can be injection-moulded with and without weld-line. Other than the four processing parameters as mentioned in previous work, another four processing parameters (mould temperature, packing pressure, injection acceleration, and packing time) were optimized to produce the moulded part with highest tensile strength. Interestingly, the experimental results showed that the melt temperature was also identified as the most influential factor on the weld-line strength out of eight processing parameters studied which is similar to the findings of previous work.

From the extensive literature reviewed, Taguchi method is a robust experimental design that seeks to obtain a best combination set of factors/levels with lowest cost solution to achieve the product quality requirements. It consists of several functional elements that can provide the necessary contribution needed to enhance the optimization implementation. Nevertheless, there are still two obvious shortcomings in performing the Taguchi method single-handedly. First, from the observations in the reviewed works, the selection of processing parameters to be optimized is totally based on the experience or literature review, which is very ineffective and unreliable. Second, when more than one quality characteristic is considered in the optimization, an engineering judgement is required to define a weight for each quality characteristic but it will increase uncertainty during the decision-making process. Hence, the integration of Taguchi method and other approaches appears to be a necessity to overcome the shortcomings of the Taguchi method and to accomplish the prerequisites of optimization effectively.

4. Integration of Taguchi Method with Various Approaches

Taguchi's contribution to the processing optimization has been far ranging as it provides a considerable reduction of time and effort needed to determine the important factors affecting product quality as well as to obtain the optimal process conditions. In order to further enhance the effectiveness and robustness of the optimization process, other approaches can be incorporated with the Taguchi method. This could allow the cross-functional integration of Taguchi method and other approaches to enrich the analysis of the optimization. The reviews presented in this research show that the statistical concepts and techniques of Taguchi method are compatible with the other approaches such as numerical simulation, grey relational analysis, principal component analysis, artificial neural network, and genetic algorithm provided that the essential variation particular to the focus of experiments is made.

4.1. Integration of Taguchi Method with Numerical Simulation. Typical numerical simulation models are developed and based on the finite element method for solving pressure, flow, and temperature fields. With the ever increasing reliance on the numerical simulation, commercial simulation packages have now become routine tools to improve the mould design and process control in injection moulding. This becomes even more significant when complicated or precise parts are produced where virtual modifications of the part and mould designs can be performed via numerical simulation. In fact, the saving of time and money for numerous modifications of part and mould designs is not trivial. Nevertheless, tremendous efforts are still required to find optimal parameters setting due to horde of simulation analyses without a systematic design of experiments. Hence, an integrated approach of coupling numerical simulation and Taguchi method is a beneficial undertaking as the former technique is capable to simulate the scenarios which are complicated to be carried out in real practice whereas the latter technique offers the advantages in abridging the simulation experiments and analyzing the results towards the optimization.

Reference [37] indicated that the integration of Taguchi method and numerical simulation offers the feasibility for investigating the effect of rib dimension and geometry on sink marks formation. ANSYS software was used to study the temperature profile inside the moulded parts for different rib geometry because the cooling rate induces the degree of crystallinity of the materials which leads to sink marks formation. It was found that the corner geometry and the width of the rib were the principal parameters affecting the sink marks of injection-moulded thermoplastic parts. Similar approach was applied by [38] where they integrated Taguchi method and ANSYS simulation to evaluate the significance of four process variables with three levels as well as the rib design on the strength of a thin beam plastic product. The deflection tests were carried out on two specimens with similar dimension, one with an optimized 10 mm reinforced rib, one without any reinforced rib, in both simulation and experiment to verify the accuracy of the optimal parameter setting and to prove the reliability of the simulation operation. The findings showed that the accuracy of the ANSYS model reaches more than 93% for both specimens, indicating high reliability of the numerical simulation in optimization.

Reference [39] used MoldFlow software to simulate the effect of different rib cross-section types and various rib layout angles on the warpage and sink index for three thermoplastics (PC/ABS, POM, and PA66). Taguchi optimization method was applied to find the optimal process parameters leading to minimum warpage and sink index and it was found that the improvement of warpage and sink index for PC/ABS, POM, and PA66 can go up to maximum 69.2% and 46.9%, respectively. In another study, [40] integrated computer aided engineering (CAE) software and Taguchi method to optimize the process variables of distance to gate and part thickness in order to produce parts with minimum sink marks. From the ANOVA, the results revealed that the part thickness is the most crucial factor because increased part thickness eases the flow to compensate for the shrinkage which produces less sink marks. It was found that the combination of CAE and Taguchi DOE is an efficient tool to investigate the effects of the factors on the part quality and optimize the process conditions and cavity geometry.

Despite of virtual modifications on part and mould designs, numerical simulation can be very useful especially when some quality characteristics involved in the study were difficult to be measured in real practice as the injection moulding is a continuous process from filling to post filling stage. The quality characteristics can be predicted via the simulation packages, including the prediction of weld-line location, shrinkage with different flow direction, and temperature gradient. Hence, the moulding conditions of the injection moulding process can be optimized via Taguchi method to improve the quality characteristics. Reference [41] explored the effect of processing parameters on the filling capability of ultra-thin wall plastic parts by combining the Taguchi method and numerical simulation. In this study, filling area was selected as the target value instead of filling volume due to the two thin parts of uniform thickness. The simulation results showed that the part thickness is the most significant parameter to the moulding of ultra-thin wall plastic parts where increasing part thickness can make a rapid increase in the filling ratio. Reference [42] has examined the warpage analysis in X-, Y-, and Z-axis by manipulating four processing parameters, including mould temperature, melt temperature, packing pressure, and packing time via MoldFlow software and applied Taguchi method to analyze the simulation results. The analysis is done for three thickness values using ABS/PC materials and the ANOVA results showed that the most influential parameter on the warpage of ABS/PC which was found to be packing pressure.

Reference [5] has applied numerical analysis in a modified L_{16} orthogonal array to systematically investigate the effects of process conditions on the shrinkage (along- and across-the-flow direction) of three plastics (HDPE, GPS, and ABS). Through C-Mold package, the results showed that different shrinkage behaviours were observed in semicrystalline plastics (HDPE) and amorphous plastics (GPS and ABS). A semicrystalline plastic shrunk more than the amorphous materials and most shrinkage occurred in the across-the-flow direction than the along-the-flow direction, but the amorphous materials showed the opposite behaviour. From the analysis, mould and melt temperatures, along with holding pressure and holding time, are the most significant influences on the shrinkage behaviours of three materials, although the importance of each is different for each plastic. Similar to previous study, [16] used C-Mold to explore the effect of four processing parameters and some interaction effects on shrinkage and warpage. It was found that the shrinkage in the X- and Y-directions under the optimal process conditions with the consideration of interaction effects was smaller than those injected under the optimal process conditions without considering the interaction effects in both prediction and verification experiments. However, there are some contradictions occurring in ANOVA indicating that all the interaction effects excluding the interaction of packing pressure and injection speed for Y-direction shrinkage were considered as insignificant factors to the quality and pooled as the error. Obviously, there are some quality improvements in the deduced optimal process conditions when the interaction effects were considered but somehow they were not of the great importance as the single processing parameters.

According to [43], experimentation with simulation models usually involves many factors. Any attempt to consider all these factors for optimization is not only uneconomical and it is also impractical since not all the factors are significant. However, the visual and numerical feedback of the process behaviour predicted by the numerical simulation can help novice engineers overcome the lack of previous experience in selecting significant parameters and assist veteran engineers in pinpointing factors that may have been overlooked. Hence, the integration of numerical simulation and Taguchi method can be used to screen the significant processing parameters in injection moulding prior the optimization if numerous processing parameters are to be considered in the optimization experiment. Reference [44] utilized C-Mold and Taguchi method to find the optimum levels of processing parameters to eliminate silver streaks on the surface of an injection-moulded polycarbonate/poly(butylene terephthalate) automobile bumper. A preliminary experiment was conducted with a L_{12} orthogonal array (OA) to screen the significant parameters prior the optimization experiment. Ten processing parameters were chosen and the effects of those parameters towards bulk temperature gradients and the mould-wall shear stress of the polymer were studied. Even though only five parameters were significantly affecting both quality characteristics simultaneously from the ANOVA results, the authors have included eight parameters in a L_{18} OA of the optimization experiment. Analysis of the experimental results revealed that the optimal processing parameters have successfully eliminated silver streaks from the injection-moulded bumpers. In another study, [45] also used two Taguchi's OA in combination with CAE based simulated experimental data for minimization of sink mark defects. The Taguchi L_8 OA was used for initial screening of seven processing variables with respect to their relative impact on the sink mark. Out of seven processing variables, only five parameters were considered as significant and allocated into a L_{27} OA for optimization. The experimental findings showed that the screening technique is achieved without affecting the adequacy of the integrated approach in prediction of the sink mark as the variation between the predicted and measured sink mark is well below 10%.

In recent years, Taguchi method has become a widely accepted methodology for improving product quality. However, the optimization design of injection moulding process parameters could be difficult as more than one quality characteristics are used in the evaluation. Problems arise whenever the optimal process parameters obtained are contradicted to each other due to different mechanisms affecting various qualities [16]. In answer to this problem, many studies devised a new experiment design methodology that optimize multiple quality characteristics simultaneously while provide accurate results to the robust design of products and process by integrating Taguchi method with other techniques.

4.2. Integration of Taguchi Method with Grey Relational Analysis (GRA). The Taguchi method is used mostly in the optimization of single quality characteristic. However, the

optimization design of injection moulding process parameters could be difficult as more than one quality characteristic are used to represent the overall quality. Hence, the GRA was first proposed by [46] to optimize the multiresponse problem by making use of the grey relational coefficient and grey relational grade. The grey relational coefficient can express the relationship between the desired and actual experimental results and the grey relational grade is simultaneously computed corresponding to each quality characteristic. In view of the fact that the distinction of GRA is attempted to integrate multiple responses, it is feasible to combine GRA with Taguchi method to provide an optimal constitute of processing parameters for the cases with multiple quality characteristics.

Few works studied the optimization of injection moulding process parameters by using the integration of Taguchi method and GRA. Reference [47] utilized the Taguchi based orthogonal array and GRA to improve the wear volume losses in two sliding directions which are parallel and perpendicular. GRA not only can be applied to obtain the optimal processing parameters which simultaneously reduced the wear volume losses in both parallel and perpendicular direction, but it can used to examine the extent to which processing parameters influence each quality characteristic based on the comparability sequence with larger value of grey relational grade in the optimization experiment. Similar to the previous work, two studies were carried out by [48, 49] using the same procedures to optimize the processing parameters for multiple quality characteristics. The former study focused on the concurrent improvement of yield stress and elongation of PC/ABS blend whereas the latter study examined the effect of processing parameters on the mechanical and tribological properties of PC composites, including ultimate stress, surface roughness, and friction coefficient.

From the reviews of the previous studies, no scientific analysis was performed on the product performance at optimal process conditions to verify the accuracy of the optimization results. Therefore, the effectiveness and reliability of the integration of Taguchi method and GRA are highly doubted and further validation of the optimization results is needed. Reference [50] optimized the processing parameters to improve the V cut depth and angle of a LCD light-guide plate and analyzed the results thoroughly based on the Taguchi method. The authors performed the main effects analysis and ANOVA to evaluate the effect of processing parameters on multiple quality characteristics instead of referring to the comparability sequence as shown in GRA. Moreover, the optimization results were further investigated through a prediction of performance at optimal process conditions and confirmation experiment to verify the accuracy and reliability of the optimization results obtained via the integration of Taguchi method and GRA. It was found that the percentage errors for the confirmation experiment values and the predicted performance values at optimal process conditions were less than 5% for both depth and angle of the LCD light-guide plate.

Some efforts have been made in coupling fuzzy logic with the integration of Taguchi method and grey relational analysis to develop a robust system for moulding parameter setting on multiple quality requirements. The theory of fuzzy logic provides mathematical strength to capture the uncertainty, ambiguity, and vagueness associated with the process of parameter setting. In the system, the inputs are the common injection moulding defects and the "fuzzified" dimensional parameters of the part while the output is the recommended adjustments of the moulding parameters. The GRA was treated as a fuzzy inference system to provide better outputs. Reference [51] studied the significance of process parameters concerning multiple quality characteristics by employing ANOVA in the application of grey-fuzzy logic on the optimal process design. The results showed that mould temperature has the most significant influence with 50.32% of percent contribution on the improvement of weld-line strength, shrinkage, and difference of forming distributive temperature. Reference [52] had studied four more process parameters including open mould time, packing pressure, packing time, and cooling time using the similar methodology. Nevertheless, the mould temperature remains the most influential factors to the weld-line strength, shrinkage, and difference of forming distributive temperature.

The greater extent of optimization was made by applying the CAE simulation to the integration of Taguchi method and GRA in order to consider the immeasurable information in the real practice, such as the distribution and variation of the temperature, pressure, flow rate, skin property, molecular orientation, shear stress, and shear rate of the material in the filling, packing, and cooling stages [11]. By applying the integration of Taguchi method and GRA, the authors [53] induced the glass fibre orientation by controlling the movement of melt flow and the mould cooling with the variation of injection moulding conditions. The findings showed that the product quality has been improved by 20% at the optimal parameter setting. With the similar integration method, [54] performed experiments on four common polymers (PP, PC, PS, and POM), comparing the effects that moulding process parameters had on their degree of warpage formation, pressure distribution, temperature distribution, and fill time of the parts. PS was found to have the smallest temperature difference which causes smaller warpage and shrinkage. However, no response value was measured in both studies instead of the conversion of factor levels of process parameters into grey relational coefficient. The work is half completed until the response values are further determined by the experienced experts. The best processing conditions were determined based on the first ranking of grey relational grade but the results of optimization can lead to the wrong conclusion if the best combination of process parameters is not either one of the experimental trials.

4.3. Integration of Taguchi Method with Principal Component Analysis (PCA). Another methodology that utilizes both Taguchi method and PCA is a practical and effective procedure for tackling multi-response problems. By using PCA, a set of original responses is transformed into a set of uncorrelated components so that the optimal factor/level combination can be found. The PCA does absolutely nothing when the responses are uncorrelated and hence the best

results are obtained when the responses or quality characteristics are highly correlated, positively or negatively [55]. The application of PCA includes a series of steps capable of solving the weakness of the standalone Taguchi method which requires engineering judgement to deal with multiple quality characteristics because an engineer's judgement increases the uncertainty during the decision-making process [56].

Reference [57] applied the PCA into Taguchi method to improve the friction properties, that is, friction coefficients and surface roughness in different sliding directions (P-type and AP-type). From the analysis of the correlation coefficient matrix, there were two of four eigenvalues larger than one. The authors have extracted the principal components and the coefficient of determination to establish a comprehensive index to obtain the final optimal parameters setting. However, no validation experiment was done to prove the effectiveness of this integrated approach. The optimization approach was further improved by [58] by combining the grey relational and principal component analyses based on Taguchi method to objectively reflect the relative importance for three performance characteristics of tensile, compressive, and flexural strength of recycled HDPE. In the study, four processing parameters including melt temperature, holding pressure, injection time, and holding time were varied via a L_9 orthogonal array to obtain optimum levels of parameters for acceptable quality. PCA was subsequently used to determine the corresponding weighting values for each performance characteristic to reflect its relative importance in the grey relational analysis. A 3×3 matrix of eigenvectors was squared to obtain the weighting values and the findings showed that the flexural strength was improved the most with contribution of 0.5274, followed by tensile strength (0.4165) and lastly compressive strength (0.057) at the optimal parameters setting.

4.4. Integration of Taguchi Method with Artificial Neural Network. Artificial neural network (ANN) is a mathematical model or computational model that tries to simulate the structure and/or functional aspects of biological neural systems. It is a multilayered architecture composed of one or more hidden layers placed between the input and output layers. The layers include processing units known as neurons. Each neuron receives total input from all of the neurons in the preceding layer and processes the input through an activation function in order to produce its output to the following layer. An ANN must be trained by methodically examining sets of input values and their associated outputs. It changes its structure based on external or internal information that flows through the network during the learning phase. A trained neural network system has the ability to transform nonlinear statistical data modelling into a simplified black-box structure that is capable of modelling complex relationships between inputs and outputs from the pattern of data.

Neural network approach was coupled with Taguchi method in building a process model for quality control in injection moulding. Reference [59] applied L_{27} orthogonal array to generate 21 training data and six testing data for a back propagation neural network (BPNN) algorithm to predict the shrinkage. ANOVA was utilized to exclude the insignificant process parameters in the prediction of neural network system to skip the vain analysis on those trivial factors. In addition, the training was performed for 500,000 cycles and the designed neural network gave a satisfactory approximation where the errors were up to 8.6%. It was mentioned that the predictability of the model could be enhanced by increasing the number of hidden layers, neurons, or cycles. However, the computational cost of the training would also increase drastically due to the complicated neural network analysis. To resolve the multi-output parameter design optimization problem, [60] formulated another type of ANN systems which is known as generalized regression neural network (GRNN) based on 16 training data from L_{16} experimental design to represent a function of three quality characteristics of a moulded part, namely, contour distortions, wear property, and tensile strength. The integrated approach managed to generate slightly better prediction results than the standalone Taguchi method, but it did not dominate in every aspect. The optimization through Taguchi-based GRNN produced better contour distortion and wear property, but the tensile strength is slightly lower compared to the optimization of standalone Taguchi method. Nevertheless, the effectiveness of optimization was still improved via the integrated approach as the operations of neural networks are in a parallel manner, their processing is fast for enhancing multiple quality characteristics simultaneously. In addition, the optimal parameters setting was not limited to only specified levels of factors but can be at any point within the level range.

Neural networks generate their own rules by learning from a certain amount of training examples [21]. However, all the efforts can be largely reduced with the aid of Taguchi method in which the case studies have been discussed previously. But still, there is no defined methodology available to help the practitioners to build a neural network model for a given problem domain. Thereby, a systematic configuration method is still lacking as there is a high degree of freedom in determining some network parameters, such as learning cycle, learning rate, momentum factor, and number of hidden neuron in advance with a trial-and-error method. It is time-consuming and low efficiency. In view of such shortcomings, [61] employed the Taguchi method to determine the configuration of learning parameters for the BPNN, to quickly find out preferable learning parameters which gave the lowest deviation before carrying out the multiple quality characteristics optimization of LCD light guide plates. It is proved that the ANN prediction system coupling with DOE method is capable of accurately predicting the quality characteristics of light guide plates with root mean square error (RMSE) which can converge to 0.00001.

4.5. Integration of Taguchi Method with Genetic Algorithms (GA). GA is one of the stochastic search algorithm inspired by evolutionary biology such as inheritance, mutation, selection, and crossover to an optimization problem evolves toward better solutions. The solution begins with a string of symbol which is called a chromosome that are randomly

generated or selected and each position of a symbol in the chromosome is called a "gene" which consists of the "allele value." The entire group of the chromosomes comprises a population. The chromosomes evolve during several iterations or generations in which the fitness of every individual chromosome in the population is evaluated and multiple chromosomes are stochastically selected from the current population based on their fitness and undergo crossover and mutation to form a new generation. Crossover involves splitting two chromosomes and then combining one half of each chromosome with the other pair. Mutation involves flipping a single bit of a chromosome where the best ones are kept while the others are discarded. The process iterated until a maximum number of generations that has been produced, or an optimum or near optimum parameter setting is found. However, if the process has terminated due to a maximum number of generations, the best solution may or may not have been reached.

From the reviews, no case study was found in relation to integration of Taguchi method with GA in optimizing the processing parameters for injection moulding. However, [62] attempted to further enhance the optimization by combining the Taguchi experimental design, ANN predictions, and GA. The integrated approach was conducted in a L_{27} experiment to result in the moulding conditions producing minimum warpage. ANOVA has successfully determined two insignificant effect parameters of minimum warpage and they were excluded in generation of ANN prediction model, and GA managed to reduce the warpage of initial model by about 51% with only 401 iterations given 2000 generations were employed. There was an argument in the paper where the response values of $A_3B_3C_2D_3E_2F_1G_3$ were conflicting to the calculation in Taguchi method wherein the actual optimal setting supposed to be $A_3B_1C_3D_1E_3F_3G_2$. In overall, the integrated approach of combining the DOE method, ANN model and GA has been proven as an effective methodology to be employed to improve the injection-moulded part quality.

5. Conclusions and Discussions

This paper presents a review of research in the optimization of processing parameters for injection moulding. A number of research works based on standalone Taguchi method and the integration of Taguchi method with various approaches, including numerical simulation, grey relational analysis (GRA), principal component analysis (PCA), artificial neural network (ANN), and genetic algorithm (GA), have been discussed. In a volatile and fiercely competitive global market, the practice of the trial-and-error approach which relies heavily on the experience of the moulding personnel is no longer sufficient to meet the challenges of globalization especially at the point where the disadvantages outweigh its advantages. In view of this, a systematic methodology exploring the relationship between parameters and identifying the optimal process conditions is proposed in the optimization of processing parameters, that is, the Taguchi method. Taguchi method is robust design techniques widely used in industries as it can improve the processing quality, reduce the number of experiments, minimize the processing variation and maintenance and promote the quality stability. However, it is realized that there is no single technique that appears to be superior in solving different kinds of problem. Improvements are to be expected by integrating the practical use of the Taguchi method into other optimization approaches to enhance the efficiency of the optimization process.

Several attempts were made in exercising the numerical simulation to define an acceptable parameter setting for the experiments which are impractical to be carried out in real practice. Due to the large number of moulding parameters involved and possible interaction among them, the optimization of processing parameters via numerical simulation requires a series of trial runs without a well-planned design of experiments. This problem has been alleviated by integrating Taguchi method with the numerical simulation to reduce the simulation experiments and analyze the results towards the optimization. On the other hand, GRA and PCA are widely integrated with the Taguchi method to tackle the multiresponse problems. In contrast the traditional Taguchi method is more to single quality characteristic optimization. Although the implementations of GRA and PCA are different, both techniques have a similarity in which the response variables are uncorrelated and hence no engineering judgement is involved during the multi-response optimization. All the computations are solely based on the formulas given and the best results are obtained when the responses or quality characteristics are highly correlated, positively or negatively where no experience and knowledge in injection moulding process are required.

Some Artificial Intelligence (AI) techniques such as ANN and GA are emerging as the new approaches in the optimization of processing parameters for injection moulding. A trained neural network system can quickly provide a set of moulding parameters according to the results of the predicted quality of moulded parts. However, the time required in the training and retraining for aneural network could be very long due to a large collection of data sets. For GA approach, the system can locally optimize the moulding parameter seven without the knowledge about the process. Nevertheless, the convergence rate to an optimal set of process parameters could be very slow in some occasions. In addition, the use of the AI techniques so far is limited to obtain the optimal process conditions as they have no statistical tool to analyze the results. By integrating Taguchi method with the AI techniques, the number of experiments is considerably reduced through the application of Taguchi's orthogonal array (OA) and the results are further being analyzed via analysis of variance (ANOVA) to determine the significance of each processing parameters on the response variables.

Taguchi method has been used for half century in the optimization of parameters of manufacturing processes; the technique itself is not new. However, a review of the literature has revealed that there are, in particular, successful industrial applications of Taguchi-based optimization approaches in determining the optimal settings of process variables for injection moulding due to its practicality and robust in

designing and optimizing the experiment. Considering the distinctive features of Taguchi method in simplifying the experiment yet leading to the accurate results, Taguchi method is not only applicable as a standalone method but it is viable to be integrated with other approaches to combine their unique features to strengthen the integrated Taguchi-based approach for truly effective optimization.

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