CHAPTER-5

STATISTICAL PROCESS CONTROL

5.1 CONTROL CHARTS

Statistical Process Control (SPC) is a systematic set of tools to solve process-related problems. Through the application of SPC tools, possible reasons that cause a process to be out of control can be identified and corrective actions can be suggested. A control chart is the primary tool of SPC and is basically used to monitor the process characteristics, e.g., the process mean and process variability [Duncan, 1988, Montgomery, 2001]. The most common types of variable control charts for variables include: (1) Average and Range (X bar and R) Charts (2) Average and Standard Deviation (X bar and S) Charts (3) Individual and Moving Range (X and MR) Charts .Collectively, the above charts are usually called Shewhart charts, as they are based on the theory developed by Dr. Walter A. Shewhart. As Shewhart charts are relatively insensitive to small shifts in the process, two more effective charts may be used to supplement them when there are small shifts in the process. (1) Cumulative Sum Control (Cusum) Chart (2) Exponentially Weighted Moving Average (EWMA) Chart [Montgomery, 2001].

The control charts in traditional SPC are designed to monitor a single product with large production runs. The availability of rational homogeneous subgroups is the basic assumption of traditional SPC. Many researchers proposed that 20-25 samples with sample size of 4-5 from a single part type should be used to calculate the meaningful control limits [Duncan, 1986, Griffith, 1996]. Therefore, at least 80- 125 units are needed for setting up a control chart. Since low-volume production does not have the aforementioned type of homogeneous subgroups, short-run SPC methods have been proposed by many researchers.

5.2. TAGUCHI METHOD

Taguchi's philosophy is an efficient tool for the design of high quality manufacturing systems. Dr. Genichi Taguchi, a Japanese quality management consultant, has developed a method based on orthogonal array experiments, which provides much-reduced variance for the experiment with optimum setting of process control parameters. Thus the integration of design of experiments (DOE) with parametric optimization of process to obtain desired results is achieved in the Taguchi method. [Datta et al.2008]

Classical experimental design methods are time consuming. Many experiments must be performed when the numbers of control factors are high [Forouraghi et al. 2002]. Taguchi methods use a special design of orthogonal arrays to study the entire factor space with only a small number of experiments. [Deng et al.2005]

The Taguchi method attempts to optimize a process or product design and is based upon three stages, as follows:

1. Concept Design or System Design
2. Parameter Design
3. Tolerance Design

The concept design is considered to be the first phase of the design strategy. This phase gathers the technical knowledge and experiences to help the designer to select the most suitable design for the intended product. In parameter design, the best setting of the control factors is determined. This is perhaps the important step, as it does not affect the unit manufacturing cost of the product. The third step is performed only after completion of the parameter design step and is exercised when further improvements are required for the optimized design. This phase focuses on the trade-off between quality and cost. However, designers in this stage consider only tightening tolerances, upgrading material standards and components, if any, having a significant impact on quality through parameter design experiments. [Jeyapaul et al.2005]

The Taguchi method uses the signal-to-noise (S/N) ratio instead of the average to convert the trial result data into a value for the characteristic in the optimum setting analysis. The S/N ratio reflects both the average and the variation of the quality characteristic. [Deng et al.2005]

The standard S/N ratios generally used are as follows: Nominal is best (NB), lower the better (LB) and higher the better (HB). The optimal setting is the parameter combination, which has the highest S/N ratio. [Datta et al.2008]

5.2.1 LARGER THE BETTER

For larger the better type characteristic S/N ratio is calculated as

S/N ratio (η) = $-10 \log_{10} (1/n\sum 1/y_i^2)$

where i=1 to n

where n = number of replications.

This is applied for problems where maximization of the quality characteristic of interest is sought. This is referred to as the larger-the-better type problem.

5.2.2 SMALLER THE BETTER

For smaller the better type characteristic S/N ratio is calculated as

S/N ratio (η) = $-10 \log_{10} (1/n\sum y_i^2)$

Where i=1to n

This is termed a smaller-the-better type problem where minimization of the characteristic is intended.

5.2.3 NOMINAL THE BEST

For nominal the best type characteristic S/N ratio is calculated as

S/N ratio (η)= $-10 \log_{10}(\mu^2/\sigma^2)$

where μ = mean

σ = standard deviation

This is called a nominal-the-best type of problem where one tries to minimize the mean squared error around a specific target value. Adjusting the mean to the target by any method renders the problem to a constrained optimization problem. [Jeyapaul et al. 2005]

Another major tool used in Taguchi design is orthogonal array, which is used to study many design parameters by means of a single response. An orthogonal array may contain both an inner array (control array) and an outer array. The inner array represents control factors involving a number of variables under the control of the experimenter. Each experimental run of the inner array is replicated according to the outer array, which is another design array based upon a certain number of noise variables for which the experimenter either cannot control directly or chooses not to control. [Jeyapaul et al. 2005]

Many Japanese firms have achieved great success by applying this method. Thousands of engineers have performed tens of thousands of experiments based on this method.

APPLICATION

Chung-Feng et al. (2006) examined multiple quality optimization of the injection moulding for Polyether Ether Ketone (PEEK). This study looked into the dimensional deviation and strength of screws produced by the injection moulding. Taguchi method was applied in this study to cut down on the number of experiments and combined grey relational analysis to determine the optimal processing parameters for multiple quality characteristics. The quality characteristics of this experiment were the screws' outer diameter, tensile strength and twisting strength. First the processing parameters that may affect the injection molding were determined with the L18 (21× 37) orthogonal, including mold temperature, pre-plasticity amount, injection pressure, injection speed, screw speed, packing pressure, packing time and cooling time. Then, the grey relational analysis, whose response table and response graph indicated the optimum processing parameters for multiple quality characteristics, was applied. This study focused on the PEEK injection moulding process using the Taguchi method and to make the experimental plan with the least number of experiments. However, the Taguchi method was used for obtaining the optimum processing combination for a single quality characteristic only, and did not give any consideration to the relationship between multiple quality characteristics and processing parameters. Therefore, the grey relational analysis was applied to improve the drawbacks of the Taguchi method and to achieve the purpose of optimization for multiple quality characteristics. As a result of the optimization of multiple quality characteristics, the dimensional deviation of the screw's outer diameter was successfully minimized, and the tensile strength and twisting strength were maximized in the meantime. In addition, a quality prediction system of the PEEK injection moulding was also established. Through the learning network, the RMSE can converge to 0.00002. The predicted values and the target values of this prediction system were all within 1.5748 %, which also shows its accuracy. It also means that the control factors and their levels as well as the learning parameters of the neural network were well planned and effectively chosen.

This also reveals the reproducibility and reliability of the experimental results. The efficiency of this optimization model had been successfully proven by experiments and can be compliant with the research purpose of taking active actions for waste prevention**.**

Dong Sung Kim et al. (2008) had experimentally characterized the transcription properties of a cross microchannel by the injection moulding process. The mould insert of the cross microchannel in the present injection moulding experiments was fabricated by UV-photolithography and the subsequent nickel electroforming processes. The parametric study of the injection moulding process was carried out by varying important processing parameters like mould temperature, injection speed, packing pressure and melt temperature. A transcription measure, relative error for width and height of the microchannel, was newly suggested to quantitatively characterize the transcription properties. The optimal and worst processing conditions were found in this study from the investigations of the injection moulded products via a scanning electron microscope and a noncontact 3D confocal microscope. From the sensitivity analysis, it was identified that the mould temperature is the most sensitive processing parameter. It was also found that the important processing parameter are mold temperature, injection speed, packing pressure and melt temperature in the order of sensitivity [Dong et al.2008].

Ziegmann et al. (2009) designed and fabricated a special mould In order to observe the developing duration of micro scale weld line during injection molding, the visualization unit was integrated in the tool. Considering the limitation of fast freezing of polymer melt during micro injection moulding, a variotherm system (fast heating/cooling system) was also arranged in this micro weld line specimen producing tool. The experiments were carried out on a horizontal injection moulding machine.

This study determined, for polypropylene (PP) material, the relation between weld line strength and processing parameters in micro injection molding based on a variothermal mold with visual structure. The optimal processing parameters and the significance order of processing parameters influencing weld line were obtained by Taguchi Analysis. Then through Chebyshev orthogonal polynomial, the four variants prediction formulation was set up for the micro injection molding weld line. By confirmation experiments it was proved that prediction errors in the model were lower than 21%.

Additionally, effects of the V notch profile on weld line strength were also studied. The results showed that V notch size in the specimens' middle part is larger and deeper than in the edge and the surface height in the middle surface is lower than in edge. The smaller V notch area also leads to a stronger micro weld line similar to macro scale case.

5.3. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial neural networks (ANNs) are defined as mathematical models which represent the biological process of a human brain. There are three main components in the ANNs; neurons or processing elements (PE), interconnections, and learning rules [Ravivongse et al.1997]. A neuron is a component that processes data. It receives and processes input signals and continually passes its output to the next level neurons. A single neuron may have more than one input but only one output. The output of a neuron depends on the input signals, weights of connections, threshold value and activation functions. The interconnection is a part of the network which propagates signals in a single direction from one neuron to the others or even to itself. The learning rules govern the change of the weight matrix in the network. Learning can be categorized into supervised and unsupervised learning. Supervised learning uses the data set that contains input vectors and corresponding output vectors to train the network while unsupervised learning relies on the local information and internal control within the network [Ravivongse et al.1997].

Artificial neural networks can be of many types like Back propogation neural network, radial basis neural network, single layer and multiple layer networks.

Neural Networks have been shown to be an effective technique for modeling complex nonlinear processes. Since the operations of neural networks are in a parallel manner, their processing is fast. Unlike some other techniques such as nonlinear regression, neural networks do not require any a priori assumptions of the function.

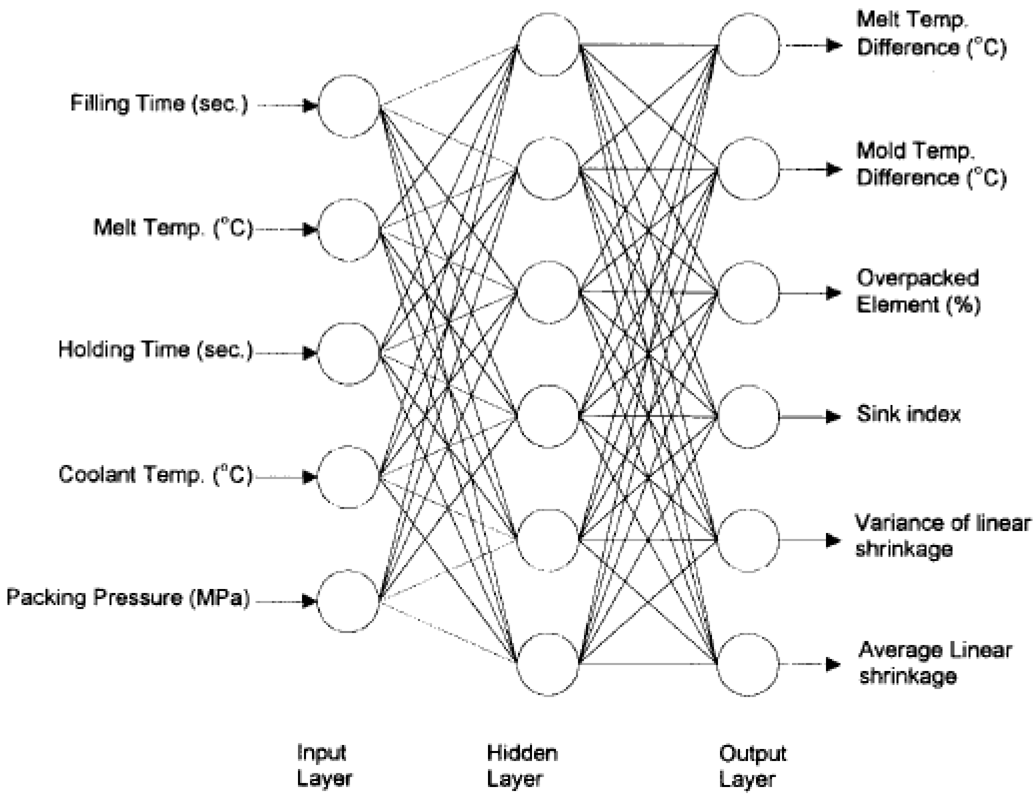

Fig.5.1- General structure of a neural network for quality prediction of moulded parts.

APPLICATIONS

Ren Shie et al. (2008) analyzed the contour distortions of polypropylene (PP) composite components applied to the interior of automobiles. Combining a trained radial basis network (RBN) and a sequential quadratic programming (SQP) method , an optimal parameter setting of the injection moulding process was determined. The specimens were prepared under different injection moulding conditions by varying melting temperatures, injection speeds and injection pressures of three computer-controlled progressive strokes. Minimizing the contour distortions was the objective of this study. Sixteen experimental runs based on a Taguchi orthogonal array table were utilized to train the RBN and the SQP method was applied to search for an optimal solution. In this study, the proposed algorithm yielded a better performance than the design of experiments (DOE) approach. In addition, the analysis of variance (ANOVA) was conducted to identify the significant factors for the contour distortions of the specimens.

A hybrid method combining a trained RBN and a SQP method to identify an optimal setting of the injection molding process of PP composite components was developed.

This study provided an algorithm that integrates a black-box modeling approach (i.e., a RBN predictive model) and a SQP method to solve a multi-output constrained optimization problem. This algorithm offered an effective and systematic way to identify an optimal setting of the injection molding process.

Hence, the efficiency of designing the optimal parameters is greatly improved. Moreover, the computational loading was trivial. The total time for training the RBN and finding an optimal solution was less than 5 minutes with a Pentium 4-M 1.7 GHz CPU computer opposed to hours of a trial-and-error method for the DOE approach in order to find significant regression models[Jie Ren et al.2008].

Rawin et al. (1997) presented a neural network-based design support tool to help designers to assess the impact of mould design on mould manufacturability (or mould complexity) before releasing the drawings to actual production. The proposed system used 14 input vectors (cost drivers) to predict mould complexity in terms of a numerical index (scale of 1- 10). Quantitative tools for mould complexity assessment help in increasing the efficiency of the product development process by reducing the number of mould design iterations made by the designer. The mould complexity index provided by the neural-net model indicates the degree of difficulty of mould complexity. It was assumed in this research that the greater the degree of difficulty the greater would be the mould manufacturing cost. However, the association (mapping) between mould complexity and mould manufacturing cost is not always linear.

Mould complexity is influenced by several factors, such as, part geometry, mould materials, parting line, and number of cavities per mould. In this study, a new design tool based on an artificial neural network (ANN) for conducting mould complexity evaluation was proposed [Ravivongse et al.1997].

5.4. FUZZY LOGIC

Fuzzy logic has great capability to capture human commonsense reasoning, decision-making and other aspects of human cognition. Kosko (1997) showed that it overcomes the limitations of classic logical systems, which impose inherent restrictions on representation of imprecise concepts. Vagueness in the coefficients and constraints may be naturally modelled by fuzzy logic. Modelling by fuzzy logic opens up a new way to optimize cutting conditions and also tool selection.

As per Klir & Yuan (1998) fuzzy logic involves a fuzzy interference engine and a fuzzification-defuzzification module. Fuzzification expresses the input variables in the form of fuzzy membership values based on various membership functions. Governing rules in linguistic form, such as if cutting force is high and machining time is high, then tool wear is high, are formulated on the basis of experimental observations. Based on each rule, inference can be drawn on output grade and membership value. Inferences obtained from various rules are combined to arrive at a final decision. The membership values thus obtained are defuzzified using various techniques to obtain true value.

APPLICATION

Joseph C. et al. (2006) described the development of a fuzzy neural network-based in-process mixed material-caused flash prediction (FNN-IPMFP) system for injection molding processes. The goal is to employ a fuzzy neural network to predict flash in injection molding operations when using recycled mixed plastics. Major processing parameters, such as injection speed, melt temperature, and holding pressure, were varied within a small range. The vibration signal data during the mold closing and injection filling stages was collected in real-time using an accelerometer sensor. The data was analyzed with neural networks and fuzzy reasoning algorithms, in conjunction with a multiple regression model, to obtain flash prediction threshold values under different parameter settings. The FNN-IPMFP system was shown to predict flash with 96.1% accuracy during the injection moulding process.

Use of neural networks and fuzzy reasoning algorithms made the FNN-IPMFP system easier to use. The FNN-IPMFP system generated accurate flash threshold values and efficiently predicted flash when major processing parameters, such as injection speed, melt temperature, and holding pressure varied within a small range.

This research is limited to only two types of plastic materials and one type of injection mold. Enlarging this system to include more materials and various molds for workpieces could provide greater applicability to future automated machining processes and implementation in industry.

5.5. GENETIC ALGORITHM

These are the algorithms based on mechanics of natural selection and natural genetics, which are more robust and more likely to locate global optimum. It is because of this feature that GA goes through solution space starting from a group of points and not from a single point. The molding conditions are encoded as genes by binary encoding to apply GA in optimization of injection molding parameters. A set of genes is combined together to form chromosomes, used to perform the basic mechanisms in GA, such as crossover and mutation. Crossover is the operation to exchange some part of two chromosomes to generate new offspring, which is important when exploring the whole search space rapidly. Mutation is applied after crossover to provide a small randomness to the new chromosomes. To evaluate each individual or chromosome, the encoded molding conditions are decoded from the chromosomes and are used to predict injection molding performance measures. Fitness or objective function is a function needed in the optimization process and selection of next generation in genetic algorithm. Optimum results of cutting conditions are obtained by comparison of values of objective functions among all individuals after a number of iterations. Besides weighting factors and constraints, suitable parameters of GA are required to operate efficiently. GA optimization methodology is based on machining performance predictions models developed from a comprehensive system of theoretical analysis, experimental database and numerical methods. The GA parameters along with relevant objective functions and set of machining performance constraints are imposed on GA optimization methodology to provide optimum processing conditions [Aggarwal et al.2005].

First of all, the variables are encoded as *n*-bit binary numbers assigned in a row as chromosome strings. To implement constraints in GA, penalties are given to individuals out of constraint. If an individual is out of constraint, its fitness will be assigned as zero. Because individuals are selected to mate according to fitness value, zero fitness individuals will not become parents. Thus most individuals in the next generation are ensured in feasible regions bounded by constraints [Jie-Ren et al.2008].

APPLICATION

Zhang et al. (2008) presented a hybrid optimal model in combination with a neural network and a genetic algorithm for the plastic injection moulding process. Computer-aided engineering (CAE) software, Mold flow, is used to simulate the flow of the plastic. Genetic algorithms (GAs), which have high capability to obtain a global optimal solution, are applied to solve the optimal model. In order to reduce the expensive computation arising from the numerical simulation, a BPNN was used to establish the approximate analysis model.

In his paper, Zhang (2003) proposed the use of a soft computing approach to the optimization of the plastic injection molding process, which combines GA and ANN. Section 2, presented the optimal mathematic model, including the selection of the objective function and the design variables. In Section 3, an optimal method integrating GAs and ANN in a soft computing paradigm was discussed. Section 4 ,provided a case study that illustrates the application of the proposed approach.

Shi et al.(2003) Focused on process operating parameters, such as mould temperature, melt temperature, injection time and injection pressure. There are other physical factors such as gating scheme design (style, size, location of the gate) and geometry of the parts that are not taken into consideration. In order to improve the capabilities of the system, a rule-based knowledge system can be incorporated into the optimization system for plastic injection molding. For future work the main concern can be towards integration of more factors. It was shown from an example that the optimization strategy is effective.

Forouraghi et al. (2000) presented a new methodology for achieving off-line quality control by employing key notions from diverse fields of evolutionary computation, multiobjective optimization and robust design. The two important quality-related activities of tolerance design and parameter optimization were addressed by using a genetic algorithm that evolves generations of hyper-rectangular design regions while simultaneously minimizing the sensitivity of the adapted designs to uncontrollable variations. Formulation of candidate designs as regions, as opposed to the traditional 'point' representation, was facilitated by a genetic coding scheme that supports interval computation.

Given an initial pool of random designs, it was demonstrated how the genetic algorithm improves the average S/N ratios of an entire population of designs from one generation to the next by conducting fractional factorial experiments. The method of non dominated sorting was employed to assign fitness values to designs based on the criterion of non inferiority. Fitter designs were selected with higher probabilities to reproduce new offspring via the standard genetic operators of reproduction, crossover and mutation. The example of multi objective design of an I-beam highlighted the advantages of using the genetic algorithm over classical min-max mathematical programming or the multi-response extension of Taguchi's method.

Forouraghi et al.2002 introduced a new method based on GAs, which addresses both the worst-case tolerance analysis of mechanical assemblies and robust design. A novel formulation based on manufacturing capability indices allows the GA to rank candidate designs based on varying the tolerances around the nominal design parameter values. Standard genetic operators are then applied to ensure that the product performance measure exhibits minimal variation from the desired target value. The computational results in the design of a clutch assembly highlighted the advantages of the proposed methodology.

The proposed algorithm was able to discover effectively in parallel optimum solutions by sampling only a small number of points per ellipsoidal design region.

The GA developed in this application focuses its search on feasible ellipsoidal design regions where a product's geometric dimensions conform to pre specified tolerances. Among many possible candidate designs in such feasible regions, the GA attempts to breed selectively fitter designs, which exhibit smaller degrees of functional variation. The discovered tight clusters in the response region correspond to robust designs where a product is designed to specifications, while its performance shows minimal sensitivity to uncontrollable parameter variations that might occur in the manufacture or life cycle of the part. The utility of the present approach was demonstrated by considering the optimal design of a clutch assembly [Forouraghi et al.2002].

5.6. FINITE ELEMENT METHOD

A variety of specializations under the umbrella of the Mechanical Engineering discipline (such as aeronautical, biomechanical, and automotive industries) commonly use integrated FEM in design and development of their products. FEM allows detailed visualization of where structures bend or twist, and indicates the distribution of stresses and displacements. FEM software provides a wide range of simulation options for controlling the complexity of both modeling and analysis of a system. Similarly, the desired level of accuracy required and associated computational time requirements can be managed simultaneously to address most engineering applications. FEM allows entire designs to be constructed, refined, and optimized before the design is manufactured.

In general, the finite element method is characterized by the following processes.

(1) First a grid is chosen. The grid consists of triangles, squares or curvilinear polygons.

(2) Then, basis functions are chosen. It can be piecewise linear basis functions or piecewise polynomial basis functions.

A separate consideration is the smoothness of the basis functions**.** In summary, benefits of FEM include increased accuracy, enhanced design and better insight into critical design parameters, virtual prototyping, fewer hardware prototypes, a faster and less expensive design cycle, increased productivity, and increased revenue.

APPLICATIONS

Lee et al. [2006] illustrated finite element and abductive neural network methods to the analysis of a multi-cavity injection mould. In order to select the optimal runner system parameters to minimize the warp of an injection mould, FEM, Taguchi's method and an abductive network were used. These methods were applied to train the abductive neural network. Once the runner and gate system parameters were developed, this network was used to accurately to predict the warp of the multi-injection mould. A simulated annealing (SA) optimization algorithm with a performance index was then applied to the neural network in order to search the gate and runner system parameters. This method obtained a satisfactory result as compared with the corresponding finite element verification.

A comparison was made between the FEM simulation mould-flow error and a model of predicted values of the optimization process. This comparison showed that the model not only fits the FEM simulation mould-flow, but also the finite element and abductive network predictions. The rapidity and efficiency of determining optimal runner system parameters for injection moulding, can successfully improve the accuracy of the injection-mould design process [Lee et al.2006].

5.7. RESPONSE SURFACE METHODOLOGY

Response surface methodology (RSM) explores the relationships between several explanatory variables and one or more response variables. The method was introduced by G. E. P. Box and K. B. Wilson in 1951. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. Box and Wilson suggested the use of a second-degree polynomial model to do this. They acknowledge that this model is only an approximation, but it is used because such a model is easy to estimate and apply, even when little is known about the process.

Response surface methodology uses statistical models, and therefore practitioners need to be aware that even the best statistical model is an approximation to reality. In practice, both the models and the parameter values are unknown, and subject to uncertainty on top of ignorance of course, an estimated optimum point need not be optimum in reality, because of the errors of the estimates and of the inadequacies of the model. Nonetheless, response surface methodology has an effective track-record of helping researchers improve products and services.

APPLICATION

Mathivanan & Parthasarathy [2009] developed a nonlinear mathematical model, in terms of injection molding variables, the model was developed using response surface methodology.

Nonlinear model for the sink depth based on central composite design of experiments, through flow simulation, was successfully developed for prediction of sink depth. To validate the model, randomly generated twenty two test cases were carried out. Deviations between predicted and actual results were found to be within ±1.4%. It shows good agreement and also the adequacy of the developed model in prediction. Though this study was conducted for the sink mark defects, evolved strategy for the study can even be extended to other defects. By applying this methodology, while designing products, corrective and iterative design steps can be initiated and implemented for improvement on product design. It can serve as tailor-made guidelines for designers.

The proposed methodology will also remove surprises during production and undue reliance on general guidelines and thumb rules. It can also be deployed for existing products for any continuous improvement

5.8. BLACKBOARD-BASED EXPERT SYSTEM AND A CASE-BASED REASONING APPROACH

This expert system includes a blackboard, a plurality of knowledge sources, a control knowledge source and a control module. The black board stores data used during an execution cycle. Each knowledge source includes rules for performing selected operations in connection with the data in the blackboard. The control knowledge source includes selection rules for selecting among the knowledge sources. The control module performing an execution cycle including an eligibility determination phase to identify one or more of the knowledge sources, a knowledge source selection phase using the selection rules and a control knowledge source to select one of the identified knowledge sources, and an action phase to process a rule of the selected knowledge source.

Case-based reasoning (CBR), broadly construed, is the process of solving new problems based on the solutions of similar past problems. An auto mechanic who fixes an engine by recalling another car that exhibited similar symptoms is using case-based reasoning. So, too, an engineer copying working elements of nature (practicing biomimicry), is treating nature as a database of solutions to problems. Case-based reasoning is a prominent kind of analogy making.

Case-based reasoning has been formalized as a four-step process:

Retrieve: Given a target problem, retrieve cases from memory that are relevant to solving it.

Reuse: Map the solution from the previous case to the target problem.

Revise: Having mapped the previous solution to the target situation, test the new solution in the real world.

Retain: After the solution has been successfully adapted to the target problem, store the resulting experience as a new case in memory.

APPLICATION

Kwong and Smitht [1998] developed computational system for the process design (CSPD) for injection moulding, called CSPD.The model has been developed based on a blackboard- based expert system and a case-based reasoning approach. Two main components of the system, the knowledge based expert system for process design (KPC) and the case based reasoning system for the process design (CBRS), have been described in detail in this paper. Blackboard architecture was used to integrate the knowledge sources needed for the accomplishment of the process design in the KPC.

The architecture was structured to be a suitable platform for organizing heterogeneous knowledge sources in an expert system to support the process design of injection moulding. The architecture allows knowledge sources to be structured in different representations, and implemented using various Artificial Intelligence (AI) paradigms. This exactly fits the characteristics of the teamwork approach to process design in which the individual might have his own style of problem solving. However, in a process design team, negotiation always happens among the team members during the design cycle. The major limitation of the blackboard architecture is its inability to support the negotiation activities among the knowledge sources. All the negotiation issues should reach the blackboard first, which would complicate the control flow for a blackboard-based system. Cooperative problem solving in a blackboard-based system may not be achieved by various knowledge sources. Sometimes, the problem-solving process has to cooperate with human experts. The realization of that requires more than a cosmetic change of classical blackboard architecture.

The implementation of CBRS demonstrates that the introduction of case-based reasoning in process design can shorten the time and simplify the process for obtaining the required setting of the Injection Moulding parameters. Possible defects, and quality information of parts can also be obtained directly without involving complicated mould flow analysis. However, the effectiveness of the CBRS is dependent on the number of relevant cases stored in the case library. If the stored cases are limited, the application of CBRS has to go through a learning curve. Another limitation of the CBRS is the lack of graphical description embedded in the cases that could affect the presentation of cases and also the evaluation of the reference case.

In comparison with existing expert systems for process design, CSPD not only allows heuristic knowledge of the injection moulding machine selection, mould base selection, production scheduling and cost estimation to be captured and represented in the KPC, but also enables weak and ill-defined knowledge, such as the setting of the injection moulding parameters and moulded part quality, to be represented easily, which is the most natural way for humans to present their experiences.

5.9. LINEAR REGRESSION MODEL

Linear regression is one of the most widely used, and most useful, statistical techniques for solving optimization problems. Linear regression models are extremely powerful and can ease complicated relationships among variables. They help to explain the relationship between dependent variable, usually denoted y, with observed values of one or more independent variables, usually denoted $x_1, x_2, ,..., x_n$. A key feature of all regression models is the error term, which is included to capture sources of error not captured by other variables. An estimator is a rule or strategy for using data to estimate an unknown parameter, and it is defined before the data are drawn. To use the ordinary least squares (OLS) estimator, the model must be linear in parameters. There are several classical assumptions outlined for the Linear Regression Method (LRM).The dependent variable (usually denoted *Y)* can be expressed as a function of a specific set of independent variables(where the function is linear in unknown coefficients or parameters) and an additive error (or disturbance) term. The coefficients are assumed to be constants, but they are unknown.

APPLICATION

Protyusha DasNeogi, and Elizabeth A. Cudney (2009) used regression analysis to compare the actual and the forecasted data. This research focuses on analyzing the predictive efficiency of the T-method and Linear Regression Method by comparing their prediction capability. The T-method, developed by Genichi Taguchi, is founded upon the fundamentals of the Taguchi System of Quality Engineering which is used to calculate an overall prediction based on signal-to-noise ratio. Using this method, the required parameters are calculated to obtain an overall estimate of the true value of the output for each signal member. Linear regression analysis is then performed on the data set. The output of this analysis is a linear equation which defines the change of the independent variable with respect to changes in the dependent variables. The strength of the relationship is then assessed using R-squared value and adjusted R-squared value. Time series analysis is also performed to predict the future values. The predicted values obtained from the resulting equation are then compared to the values obtained by the T-Method. A case study of country food self-sufficiency is used for comparison and to demonstrate the benefits and limitations of each method.

The $R^2$and adjusted R^2 values obtained by Taguchi method are 0.95 and 0.89 whereas that obtained by linear regression method is 0.982 and 0.962 respectively. The R-Squared value obtained using the linear regression method is greater than that obtained by Taguchi method. For this case study, therefore, the predictions obtained by the linear regression method produce a higher correlation.

5.10. GREY RELATIONAL ANALYSIS

In Grey relational analysis, experimental data i.e., measured features of quality characteristics are first normalized ranging from zero to one. This process is known as Grey relational generation. Next, based on normalized experimental data, Grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall Grey relational grade is determined by averaging the Grey relational coefficient corresponding to selected responses. The overall performance characteristic of the multiple response process depends on the calculated Grey relational grade. This approach converts a multiple response process optimization problem into a single response optimization situation. The optimal parametric combination is then evaluated which would result in highest Grey relational grade. The optimal factor setting for maximizing overall Grey relational grade can be performed by Taguchi method [Datta et al.2008].

APPLICATION

Chung-Feng et al. (2006) focused on the PEEK injection molding process using the Taguchi method and to make the experimental plan with the least number of experiments. However, the Taguchi method was used for obtaining the optimum processing combination for a single quality characteristic only, and did not give any consideration to the relationship between multiple quality characteristics and processing parameters. Therefore, the grey relational analysis was applied to improve the drawbacks of the Taguchi method and to achieve the purpose of optimization for multiple quality characteristics. As a result of the optimization of multiple quality characteristics, the dimensional deviation of the injection moulded screw's outer diameter was successfully minimized, and the tensile strength and twisting strength of the screw were maximized in the meantime. In addition, a quality prediction system of the PEEK injection moulding was also established.

The above study combined grey relational analysis with the Taguchi method for the optimization of the PEEK injection molding processing parameters. The efficiency of this optimization model had been successfully proven by experiments and could be compliant with the research purposes of taking active actions for waste prevention.

Chung-Feng et al. (2006) applied grey relational analysis to obtain the optimum processing conditions for multiple quality characteristics. The target value of the hexagonal screw's outer diameter and the maximum mean values of the tensile strength and twisting strength of L18 orthogonal array were used for the reference sequence. The calculation results of the differential sequence, the grey relational coefficients and grades in each experiment in the reference sequence and orthogonal array were depicted in response table.

From the response table and the response graph of the above analysis, the optimal processing conditions of the PEEK injection molding for the hexagonal screw were mould temperature at 160^{0}C, pre-plasticity amount of 5 cm, injection pressure of 250 bar, injection speed of 15 cm/sec, screw speed of 25 m/min, packing pressure of 600 bar, packing time of 3 sec and a cooling time of 15 sec.

While with only a single quality characteristic, when the screw's outer diameter, was taken into consideration, the optimum processing conditions were mould temperature at 160^{o}C, pre-plasticity amount of 6 cm, injection pressure of 450 bar, injection speed of 15 cm/sec, screw speed of 25 m/min, packing pressure of 400 bar, packing time of 9 sec and a cooling time of 5 sec [Feng et al.2006].

5.11. CAVITY PRESSURE SIGNALS AND PRINCIPAL COMPONENT ANALYSIS

Principal component analysis (PCA) involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA is theoretically the optimum transform for given data in least square terms. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data.

APPLICATION

Jin Zhang and Alexander proposed a novel application of pattern recognition for process fault diagnosis. Mould cavity pressure signals from a plastic injection molding process facilitate process monitoring and diagnosis. Principal component analysis is applied to cavity pressure signals to reduce dimensionality while preserving the characteristics of the original signals. Process "fingerprints" were developed via wavelet decomposition of the "reduced" signal using multi resolution analysis. These fingerprints can be interpreted via artificial neural networks for process condition monitoring and fault diagnosis. The diagnostic system can be updated adaptively as new process faults are identified.

In this paper, Jin Zhang demonstrated the feasibility of using cavity pressure signals and PCA for fingerprinting the injection moulding process and fault diagnostic system development. Once the faults are diagnosed, the control variable settings can be adjusted to make the cavity pressure profile uniform for the consistent part quality. The results showed that this diagnostic approach is efficient for use in the process monitoring, diagnostics and control [Jin Jhang et al.].

Table 5.1 gives summary of all the above injection moulding processes along with tools used and remarks.

Table 5.1. Summary of plastic injection molding optimization techniques.

Technique	**References**	**Tools used**	**Remarks**
Taguchi technique	Chung-Feng ,Jeffrey Kuo and Te-Li Su (2006)	Design of experiments, Orthogonal arrays, ANOVA	Based on actual experimental work and determination of optimum conditions using statistical tools
Artificial Neural Networks (ANN**)**	Jie-Ren Shie (2008)	Combining a trained radial basis network (RBN) and a sequential quadratic programming (SQP)	Optimal parameter setting of the injection moulding process was determined.
Fuzzy logic	Jie Zhu , Joseph C. Chen (2006)	Fuzzy interface engine & fuzzification–defuzzification module	Based on a model which works on human common-sense reasoning, decisionmaking and other concepts of human cognition.
Genetic algorithm	F. Shi, Z. L. Lou, J. G. Lu ,Q. Zhang (2003)	A CGI (common gateway interface) program	Based on model developed from theoretical analysis, experimental database and numerical methods.

Finite Element Method	K.S. Lee and J.C. Lin [2006]	Finite element and abductive neural network methods for the analysis of a multi-cavity injection mould	A simulated annealing (SA) optimization algorithm with a performance index is applied to the neural network in order to search the gate and runner system parameters.
Response surface methodology	D. Mathivanan & N. S. Parthasarathy [2009]	Design expert software (DX6)	Based on a injection moulding model developed by mathematical and statistical techniques
Blackboard-Based Expert System and a Case-Based Reasoning	C. K. Kwong* and G. F. Smitht [1998]	Computational system for the process design (CSPD) for injection moulding	CBRS demonstrates that the introduction of case-based reasoning in process design can shorten the time and simplify the process for obtaining the setting of injection moulding parameters

Linear regression model	Protyusha DasNeogi, and Elizabeth A. Cudney (2009)	Ordinary least squares (OLS) estimator and an additive error (or disturbance) term	Output of this analysis is a linear equation which defines the change of the independent variable with respect to changes in the dependent variables.
Grey relational analysis	Chung-Feng Jeffrey Kuo and Te-Li Su (2006)	Combined grey relational analysis with the Taguchi method	Optimal processing conditions of the PEEK injection moulding for the hexagonal screw
Cavity Pressure Signals and Principal component analysis	Jin Zhang and Suraj M. Alexander	Mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables	Proposed a novel application of pattern recognition for process fault diagnosis. Mould cavity pressure signals from a plastic injection moulding process facilitate process monitoring and diagnosis