Chapter 13
Taguchi Method Using Intelligent Techniques

Kok-Zuea Tang, Kok-Kiong Tan and Tong-Heng Lee

Abstract The Taguchi method has been widely applied in quality management applications to identify and fix key factors contributing to the variations of product quality in manufacturing processes. This method combines engineering and statistical methods to achieve improvements in cost and quality by optimizing product designs and manufacturing processes. There are several advantages of the Taguchi method over other decision making methods in quality management. Being a well-defined and systematic approach, the Taguchi method is an effective tuning method that is amenable to practical implementations in many platforms. To build on this, there are also merits, in terms of overall system performance and ease of implementation, by utilizing the Taguchi method with some of the artificial intelligent techniques which require more technically involved and mathematically complicated processes. To highlight the strengths of these approaches, the Taguchi method coupled with intelligent techniques will be employed on the fleet control of automated guided vehicles in a flexible manufacturing setting.

Keywords Taguchi method · Artificial intelligent techniques · Automated guided vehicles

13.1 Introduction

Taguchi method is an experimental design method that has been developed by Dr. Genichi Taguchi (1993). It is called quality engineering (or Taguchi methods in the United States). The Taguchi method combines engineering and statistical methods

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(Mori 1993; Ealey 1994) to achieve improvements in cost and quality by optimizing product design and manufacturing processes. The main advantage of Taguchi method over other search and tuning method is the twofold benefit of both efficiency and simplicity. Efficiency provides an affordable avenue for problem solving. Simplicity results in a set of tools more easily adopted and embraced by the non-statistical expert.

Conventionally, the Taguchi method has been widely applied in quality control applications to identify and fix key factors contributing to the variation of product quality in manufacturing process (Peace 1993; Ross 1988; Hong 2012; Rao et al. 2008; Taguchi et al. 2004; Chen et al. 1996). These successful quality management applications can be found in a diverse range of industries, ranging from chemical plants, electrical and electronics manufacturing, mechanical productions, software testing, and biotechnology-related fields like fermentation, food processing, molecular biology, wastewater treatment and bioremediation biological sciences.

There are several strengths of the Taguchi method that is worth mentioning here (Ealey 1994; Peace 1993). The Taguchi method is an effective tuning method that has well-defined, systematic and simple steps. The optimum values of the factors to be tuned are determined in relatively shorter and limited steps. All the above mentioned points make the Taguchi method amenable to practical implementation. Some of the artificial intelligent methods, like the genetic algorithm, the neural networks and the evolutionary algorithm, propose more involved and complicated search methods for optimization (Tortum et al. 2007). Furthermore, the Taguchi method selects a combination of the factors (i.e., that needs to be tuned) that are robust against the changes in the environment. The Taguchi method has the additional advantage of being amenable to analyzing the sensitivity of the individual factor that is to be tuned on the final objective performance. The above mentioned artificial intelligent methods, on the other hand, are not able to provide this analysis. In this perspective, there are some merits in utilizing the Taguchi method together with some of these artificial intelligent methods.

In the current literature, researchers and engineers have also built on the successful track records of the Taguchi method. Being an optimization tool that is amenable to practical implementation, the Taguchi method is able to complement the strengths of various tools in artificial intelligence (Tortum et al. 2007; Chang 2011; Ho et al. 2007; Yu et al. 2009; Khaw et al. 1995; Hissel et al. 1998; Tsai 2011; Chou et al. 2000; Hoa et al. 2009; Woodall et al. 2003; Hwang et al. 2013; Huang et al. 2004; Tan and Tang 2001). For example, Hissel et al. have evaluated the robustness of a fuzzy logic controller using the Taguchi quality methodology and experimental product-plans (Hissel et al. 1998). The Taguchi method provides an effective means to enhance the performance of the neural network in terms of the speed for learning and the accuracy for recall (Tortum et al. 2007; Khaw et al. 1995). The determination of the parameters in engineering systems can be improved using hybrid methods that employ evolutionary algorithms, genetic algorithms and the Taguchi method (Chang 2011; Yu et al. 2009).

It is to be noted that the Taguchi method has some weak areas in comparison to some of the above mentioned artificial intelligent methods, as a search and tuning method. Due to the simplicity of the Taguchi method, it may not be as effective in situations where the search region is complicated. Also, Taguchi method may not be as precise a tuning method, as compared to the more elaborate artificial intelligent methods (Chang 2011).

In this chapter, a brief overview of the Taguchi method will first be provided, focusing on the practical aspects of applications. Leveraging on the quality methodology of the Taguchi method, hybrid approaches of combining the strengths of the Taguchi method with intelligent techniques like the fuzzy logic and the neural network. The case study at the end of the chapter will provide simulation results of applying the Taguchi method and the hybrid approaches (i.e., combining the Taguchi method with artificial intelligence) on the fleet control of automated guided vehicles (AGVs) in a flexible manufacturing setting.

13.2 Taguchi Method

The Taguchi method is a statistical search for a set of optimum factors that could affect the quality outcome of a process or final product. Given a problem, the objective value is expressed as a quality characteristic, i.e., productivity, durability, number of products completed in a given duration of time, etc. The scaling factors are referred to as the control factors in the Taguchi method. Determination of the optimum values of the control factors occurs during the experimental design phase. In this phase, the different combinations of the control factors are used in the runs to investigate their effects on the final quality characteristic. The results of the experiments are then used to adjust the control factors for iteratively improved performance.

13.2.1 Selection of Quality Characteristics

Quality characteristics may be classified into a few general categories such as smaller-the-better (STB), larger-the-better (LTB) or nominal-the-best (NTB). For a given problem, a number of measures of the quality characteristics are possible and associated with the nature of the problem itself.

13.2.2 Control Factors and Levels

The control factors are to be tuned by the Taguchi method for optimal performance. The number of levels of each control factor is the number of different values that are to be assigned to the control factor. The number of levels for each factor is assigned to be two, three or four (Mori 1993), depending on the nature of the overall problem. Using a larger number of levels reduces the number of control factors that are can be effectively analyzed.

13.2.3 Selection of Orthogonal Array and Linear Graph

For the control factors considered, it will not be practically possible to analyze the effects of all the different combinations on the quality characteristic, as in a full factorial experimental design (Mori 1993) in a practical sense. Given the constraints, the optimum levels of the control factors must be determined using a practical and limited number of experiments on a rich sample of the possible combinations. While this set may be generated by a random parameter picking procedure, there is little assurance that the thus generated set will offer a good variation of possibilities within the finite set.

To this end, a special table called the orthogonal array due to Fisher (Ealey 1994) is used to generate an efficient set of parameters for experimentation. By drawing a relatively small amount of data which are statistically balanced and independent, meaningful and verifiable conclusions can be derived from the orthogonal array. Complete compilation of orthogonal arrays can be easily available (Mori 1993; Ealey 1994).

One of the main steps in the experimental design is to choose the most appropriate orthogonal array for the particular problem. There are many issues to be considered in the final selection, i.e., the number of control factors, the number of levels of the control factors, number of interactions of interest, etc. After the orthogonal array is selected, the linear graph (Peace 1993) may be used to assign the control factors and interactions to the appropriate columns of the orthogonal array. Incorrect analysis and faulty conclusions may result if the control factors and interactions are assigned to the any columns of the orthogonal array. By using the linear graph, a systematic way of assigning the control factors and interactions to the respective columns of the orthogonal array is developed by Taguchi. The linear graph is made up of nodes and connecting arcs. The nodes represent the control factors and the arcs represent the interactions or the relationship between the control factors.

The systematic experimentation procedure of the Taguchi method can be summarized as follows:

1. Determine the number of factors and interactions to be considered in the experiment and the number of levels (i.e., or values) of the factors. Typically, the number of levels of the factors is two or three.
2. Select the appropriate orthogonal array.
   (a) Determine the required degrees of freedom (DOF) (Peace 1993) from the factors and interactions. The DOF of a factor is one less than the number of levels of the factor. The DOF of a particular orthogonal array is obtained by the sum of the individual DOF for each column in the array.

(b) The appropriate orthogonal array is the one with has the DOF that is equal to or more than the required DOF of the factors. The smallest array satisfying this requirement is normally chosen for efficiency.

3. With the appropriate orthogonal array chosen, choose the linear graph that fits the relationships of the factors of interest. The factors can then be assigned to the columns of the orthogonal array according to the linear graph.
4. Conduct the experiments and analyze the results.
5. Finally, run a confirmation experiment using the results obtained.

13.2.4 Interpretation and Validation of Experimental Results

After the experimental data from the set of weighting parameters is obtained, there are various approaches to verify the results. One of the common approaches adopted by the industry is to use past data published in the literature. To provide a more systemic approach, statistical tools like the F-test and the T-test could be used to interpret the experimental data mathematically and to provide indications of whether the decision related to the management of the quality is adequate and if further tuning is necessary to improve the quality of the final output (Mori 1993).

13.2.5 Literature Review on Taguchi Method

In the literature, there are many applications using the Taguchi method. These applications include a wide range of fields, from manufacturing processes to design and development of systems and devices. The publication frequencies of the Taguchi method for the past decade (i.e., from 2004 to 2013) are shown in Fig. 13.1. There has been increasing interests on the Taguchi method, since Dr. Genichi Taguchi introduced this practical statistical tool in the 1980s to improve the quality of manufactured goods. These publications are in the form of journal articles, books, technical notes and theses. The different publication categories on the Taguchi method for the past decade are shown in Fig. 13.2.

It is to be noted that these publications focus heavily on the application and verification of the Taguchi method. For example, Sreenivasulu (2013) employed the Taguchi method to investigate the machining characteristics on a glass fiber reinforced polymeric composite material (GFRP) during end milling. He then used the ANOVA method to verify significant parameters and confirm the optimum values obtained by the Taguchi method. These results are even compared with the neural networks tuning method. The results show that the Taguchi method and the neural networks produce very similar results. The Taguchi method is also employed to

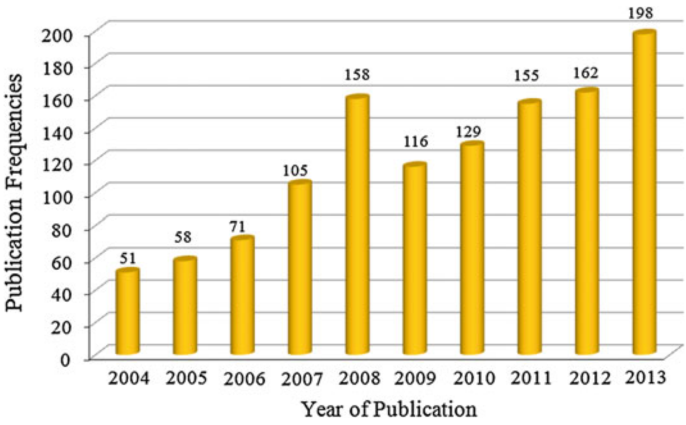


Fig. 13.1 Publication frequencies of the Taguchi method for the past decade (i.e., from 2004 to 2013)

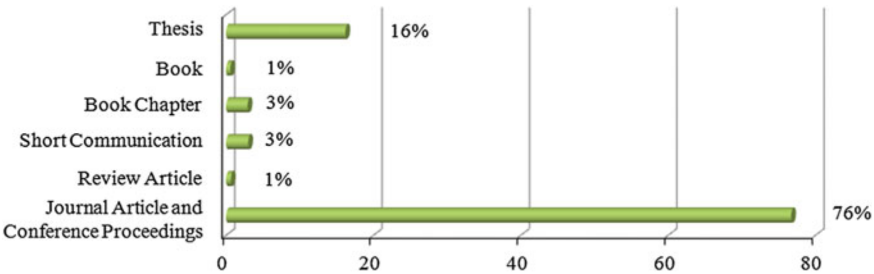


Fig. 13.2 Publication categories on the Taguchi method for the past decade (i.e., from 2004 to 2013)

understand the fermentative hydrogen production process (Wang and Wan 2009). The effects of the various factors in this complex process could be investigated and analyzed using the Taguchi method. The results of this work highlights that the simplicity of the Taguchi method is an advantage over other more involved optimization tools. Asafa and Said (2013) integrates the Taguchi method and the neural networks together to model and control the stresses induced during the plasma enhanced chemical vapor deposition process on hydrogenated amorphous silicon thin films. The Taguchi method with ANOVA is able to obtain the significance of the various network parameters on the overall model. Using these significances, the authors are able to verify the trend between the deposition parameters and the resulting intrinsic stresses during the process. The obtain results concur with other published data in the literature on plasma enhanced chemical vapor deposition process. In a similar way, there are other works in the literature that integrate the Taguchi method with other tools in artificial intelligence (i.e., genetic algorithm, neural networks, fuzzy logic and regression analysis) to optimize other processes and systems (Lin et al. 2012; Sun et al. 2012; Mandal et al. 2011; Chang 2011; Tsai 2011; Tansel et al. 2011; Tzeng et al. 2009). In Lin et al. (2012), the Taguchi method is integrated with the neural networks and the genetic algorithm to improve a particular manufacturing process of the solar energy selective absorption film. For this problem, the Taguchi method is able to perform well to optimize a given search space; whereas the genetic algorithm and other evolutionary numerical methods can be used to control a poorly defined search space. The results in the literature show that the integrated approach of the Taguchi method with other artificial intelligence tools produces better results than just utilizing a single optimization tool alone.

Besides modeling and optimizing manufacturing processes, the Taguchi method has also been widely applied in other fields, like the supply chain management (Yang et al. 2011) and clinical diagnostics (De Souza et al. 2011). Yang et al. (2011) used the Taguchi method to study the robustness of different supply chain strategies under various uncertain environments. The complexity of the problem is accentuated by the variations in the business environments. The performance of the Taguchi method is shown to compare well with other multiple criteria decision-making techniques, like the simple multiple attribute rating technology (SMART), the technique for order performance by similarity to ideal solution (TOPSIS), and grey relational analysis (GRA). The Taguchi method is utilized to optimize the Molecular assay for venous thrombo-embolism investigation (De Souza et al. 2011). There are various risk factors that are patient-dependent and render the investigation process uncertain and difficult. The application of the Taguchi method can lessen the time and cost necessary to achieve the best operation condition for a required performance. The results is proven in practice and confirmed that the Taguchi method can really offer a good approach for clinical assay efficiency and effectiveness improvement even though the clinical diagnostics can be based on the use of other qualitative techniques.

13.3 Tuning Fuzzy Systems Using the Taguchi Method

The statistical potential of the Taguchi method can be harnessed to tune the performance of many intelligent systems. As highlighted briefly in Sect. 13.2.5 above, there are other works in the literature that integrate the Taguchi method with other tools in artificial intelligence (i.e., genetic algorithm, neural networks, fuzzy logic and regression analysis) to optimize other processes and systems (Lin et al. 2012; Sun et al. 2012; Mandal et al. 2011; Chang 2011; Tsai 2011; Tansel et al. 2011; Tzeng et al. 2009). The results show that the integrated approach of the Taguchi method with other artificial intelligence tools produces better results than just utilizing a single optimization tool alone.

In this section, the integration of the Taguchi method with fuzzy systems will be described in details to show how these two methodologies can be utilized to complement each other. The work of Zadeh (1973) provides a comprehensive review on fuzzy logic, as an alternative branch of mathematics.

In a fuzzy system, the objects are associated with attributes. These attributes can be computed from fuzzy operations on a combination of variables which are used to describe mathematically the real-time conditions of the given problem. Decisions that affect the system's performance will be driven primarily by these attributes.

To incorporate the Taguchi method into the fuzzy system, the fuzzy system has to be posed as a quality control scenario, with appropriate performance measures as the quality characteristics. The Taguchi method then can be utilized to tune the parameters in the fuzzy rules in the inference engine.

13.3.1 Takagi and Sugeno's Fuzzy Rules

To illustrate how the Taguchi method could be used to tune fuzzy systems, the K attributes will be inferred from a Takagi and Sugeno type of fuzzy inference (Takagi and Sugeno 1985). Consider the following p rules governing the attribute a_k:

$$IF\ x_{k1}^i\ is\ F_1^i\ \otimes \cdots \otimes\ IF\ x_{km_i}^i\ is\ F_{km_i}^i,\ THEN\ u_k^i\ is\ \alpha^i, \quad i = 1\ldots p. \tag{13.1}$$

with $\sum_{i=1}^{p} \alpha^i$ and $k = \{k \in \mathbb{Z}\ |0 \le k \le K\}$, where F_j^i are fuzzy sets, $\boldsymbol{x}^i = \left[x_{k1}^i, \ldots, x_{km_i}^i\right]^T \in \mathbb{R}$ are the input linguistic variables identified to affect the attribute for rule i, $\otimes$ is a fuzzy operator which combine the antecedents into premises, and u_k^i is the crisp output for rule i. α^i is the scaling factor for rule i reflecting the weight of the rule in determining the final outcome.

The value of each attribute a_k is then evaluated as a weighted average of the u^i's.

$$a_k = \frac{\sum_{i=1}^{P} w_k^i u_k^i}{\sum_{i=1}^{P} w_k^i} \tag{13.2}$$

where the weight w_k^i implies the overall truth value of the premise of rule i for the input and is calculated as:

$$w_k^i = \prod_{j=1}^{m} \mu_{F_{kj}^i} x_{kj}^i \tag{13.3}$$

13.3.2 Incorporating Fuzzy Logic with Taguchi Method

In a fuzzy system, the approach to the decision making is based on a fuzzy inference engine which is able to specialize in a multiple criteria satisfaction. The overall effectiveness of this fuzzy logic approach in a given scenario is critically dependent on the appropriateness of the fuzzy rules, in particular, the weight or the scaling factors of each of the fuzzy rules on the final decision. One of the main issues is to address the selection of the scaling factors, i.e., α's in Eq. (13.1). By a manual trial-and-error adjustment method, the search for the optimal set is by far too tedious and time consuming. On the other hand, an exhaustive search for the optimal set of scaling factors would be unrealistic and impractical. To this end, a systematic search procedure within a balanced set of possible weighting parameters will be both desirable and practical. The Taguchi method would be an ideal candidate that could be deployed to obtain the optimal set of the scaling factors for the fuzzy rules.

The main strength of the Taguchi method over other search and tuning methods is the twofold benefit of both efficiency and simplicity. Efficiency provides an affordable avenue for problem solving. Simplicity results in a set of tools more easily adopted and embraced by the non-statistical expert. The quality characteristics used in the Taguchi methodology may be classified into a few general categories such as smaller-the-better (STB), larger-the-better (LTB) or nominal-the-best (NTB). For a given problem, usually a number of measures of the quality characteristics are possible and associated with the nature of the problem itself.

To determine the control factors and the assigned levels, the scaling factors associated with the attributes in the fuzzy rules are the control factors to be tuned by the Taguchi method for optimal performance. The number of levels of each control factor is the number of different values that are to be assigned to the control factor. The values are dependent upon the constraints (i.e., which could be related to the hardware and other constraints of the system) of the given problem. In the next section, the case studies will demonstrate the potential of the Taguchi method combined with the fuzzy system.

13.4 Using Taguchi Method with Neural Networks

To explore further the potential of the Taguchi method as a search and tuning method, the Taguchi method is applied together with another intelligent method, i.e., neural network system, for quality management. Neural networks are inherently useful for approximating non-linear and complex functions. This is especially true for functions when only the input/output pairs are available and the explicit relationships are unknown. Considering such strengths, neural networks could be good candidates for quality management problems, like monitoring and controlling quality-critical processes with complex system dynamics in the manufacturing environment. This is because such processes display non-linear behavior and it is very difficult to obtain closed-form models of such processes to describe the overall system characteristics and dynamics perfectly. By gathering input and output data pairs of such processes, neural networks could be employed to model the process and provide corrective control action in various manufacturing environments, requiring quality management.

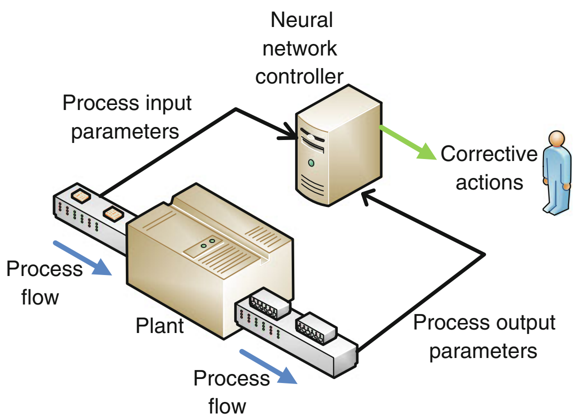
Artificial neural networks are an alternative computing technology that have proven useful in a variety of pattern recognition, signal processing, estimation, and control problems. Indeed, many real-world processes are multidimensional, highly non-linear and complex. It is extremely difficult and time-consuming to develop an accurate analytical model based on known mathematical and scientific principles. Moreover, it is often found that the simplified analytical model is not accurate enough to model these complex processes, resulting in poor performance or results. Artificial neural networks allows one to consider them as a black box can be taught using actual data to act as the accurate model for the processes (Haykin 1994).

There are two common configurations which we could utilize neural networks for quality management (Figs. 13.3 and 13.4). In Fig. 13.3, the neural network 'learns' the process dynamics using input/output data pairs. This type of learning is done using past batches of input/output data pairs to tune the neural network's parameters. This neural network can then be used to monitor the performance of the process during the manufacturing cycle. Corrective actions in the form of user alerts will be invoked whenever, the output of the process deviates from a known pattern or when other abnormal conditions are detected by the neural network controller.

Besides the configuration shown in Fig. 13.3, the neural network could also be incorporated into the process control loop as shown in Fig. 13.4. Here, the neural network provides control actions that adapt to changes in the system output during the process run. The learning phase of the neural network could be online or offline. Online learning of the neural network refers to tuning of the internal parameters while the process is given new inputs; whereas offline learning refers to tuning of the neural network's parameters using past batches of input/output data pairs.

In both configurations shown in Figs. 13.3 and 13.4, the effectiveness of the neural network relies critically on how well it is trained. Training of the neural network can be seen as allowing its parameters to learn the patterns of the process using input/output data pairs. The neural network is then able to model the

Fig. 13.3 Utilizing neural networks for quality management with the controller outside the control loop



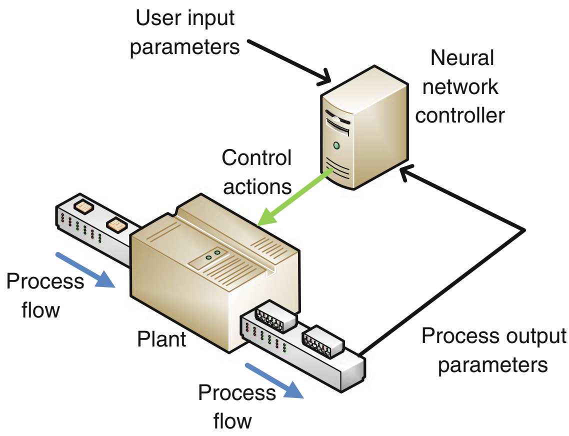


Fig. 13.4 Utilizing neural networks for quality management with the controller integrated within the control loop

non-linear and complex function that represents the input/output data pairs. This training process may entail an exhaustive search for optimum weights, using a conventional Newton-Raphson type of gradient search (Haykin 1994), or adopting a backpropagation approach (Zurada 1992). The effectiveness of these approaches is highly dependent on the proximity of the initial set to the optimum set, and typically a localized optimum point can be located at best.

As highlighted briefly in Sect. 13.2.5 above, there are other works in the literature that integrate the Taguchi method with other tools in artificial intelligence (i.e., genetic algorithm, neural networks, fuzzy logic and regression analysis) to optimize other processes and systems (Lin et al. 2012; Sun et al. 2012; Mandal et al. 2011; Chang 2011; Tsai 2011; Tansel et al. 2011; Tzeng et al. 2009). The results show that the integrated approach of the Taguchi method with other artificial intelligence tools produces better results than just utilizing a single optimization tool alone. It would be interesting to compare the results of integrating the Taguchi method with the neural networks. For illustration purpose, a radial basis function neural network (RBFNN) is used in this section to show how the Taguchi method can be used effectively with neural networks for process control applications. RBFNNs are one popular and commonly used configuration of neural networks (Haykin 1994; Zurada 1992). RBFNNs use a set of basic functions in the hidden units. Other types of neural networks could use different types of functions in the hidden units. The training process of the different types of neural networks may differ in the methodology. But the objectives are the same, i.e., that is to improve the performance of the neural network when the network is deployed for its purpose. More details of the different types of neural networks could be found in Haykin (1994).

As mentioned earlier, the effective modeling of the given functions entails training the RBFNNs which, in turn, filter down to proper selection and tuning of the parameters (i.e., weighting factors) in the RBFNNs. This training process may entail an exhaustive search for optimum parameters. The effectiveness of the tuning approach is highly dependent on the proximity of the initial set to the optimum set, and typically a localized optimum point can be located at best. The effectiveness and success of the Taguchi statistical method in experiment design to yield an optimum result is well demonstrated and proven in many cases. Considering complex processes in quality management, Taguchi-tuned neural networks could provide good solutions for control and monitoring applications. In the following, the application of the Taguchi method to RBFNN tuning is briefly discussed.

13.4.1 Taguchi Method Applied to RBFNN Tuning

In this section, the Taguchi method is used to obtain optimum weights associated with a RBFNN which is used for the purpose of modeling uncertain nonlinear functions which are subsequently applied for process control. Conventionally, these weights are obtained via an exhaustive search or a localized search using an iterative gradient search algorithm.

To state the problem for the RBFNN, $f(\boldsymbol{x})$ is a nonlinear smooth function (i.e., which is unknown) which can be represented by

$$f(\boldsymbol{x}) = \sum_{i=0}^{m} w_i \emptyset_i(\boldsymbol{x}) \tag{13.4}$$

where $\emptyset_i(\boldsymbol{x})$ denotes the RBF, i.e.,

$$\emptyset_i(x) = \exp\left(-\frac{|\boldsymbol{x}-c_i|^2}{2\sigma_i^2}\right) \Big/ \sum\nolimits_{j=0}^{m} \exp\left(-\frac{|\boldsymbol{x}-c_j|^2}{2\sigma_j^2}\right) \tag{13.5}$$

where the vector $\boldsymbol{x}$ represents the states of the system. The ideal weights are bounded by known positive values such that

$$|w_i| \le w_M \tag{13.6}$$

where $i = \{i \in \mathbb{Z} \mid 0 \le i \le m\}$. Let the RBF functional estimates for $f(\boldsymbol{x})$ be given as:

$$\widehat{f}(\boldsymbol{x}) = \sum_{i=0}^{m} \widehat{w}_i \emptyset_i(\boldsymbol{x}) \tag{13.7}$$

where $\widehat{w_i}$ are the estimates of the ideal RBF weights.

Therefore, there are (m + 1) parameters (i.e., or weights) to be tuned. It is a difficult *NP*-complete problem to determine the optimum weights especially for large m. A gradient search method is sometimes used, which is sensitive to the initial set selected and is faced with a convergence problem. Even if the search is convergent, usually only a localized optimum point is obtained. The Taguchi method can thus be applied to systematically search for the optimum set.

As mentioned earlier in this chapter, quality characteristics in a Taguchi experiment refer to the assessment factors which are used for measuring how good the objectives of the experiment are met. For machine learning, the quality characteristic can be based on an appropriate measure of the deviation of the RBFNN from the actual nonlinear function, i.e., the residue. Since the objective here is for the RBFNN to approximate the actual function closely, this measure is desired to be as small as possible (i.e., smaller-the-better, STB). Even then, the quality characteristic can also be formulated in various ways, e.g., maximum error, sum of absolute error, sum of squares of error, etc.

The control factors are the parameters to be tuned using the Taguchi method. Clearly, the weights of the RBFNN are the control factors of the Taguchi experiment. Depending on the number of control factors and assigned levels in the RBFNN, the appropriate orthogonal array and linear graph can be used to generate an efficient set of parameters for experimentation. The systematic experimentation procedure of the Taguchi method can then be employed for tuning the neural networks. The testing and validation process of the neural network (which employed the Taguchi method for training purpose) is the same as that when the other conventional training methods, like the back propagation and other gradient-based methods, are employed. The main advantage of employing the Taguchi method for training the neural network is to provide a systemic view for the search space. Problems encountered by neural networks employing the traditional methods, such as over-training and local minima, could be avoided.

13.5 Case Studies

In this case study, we would like to study the performance of integrating Taguchi method with another artificial intelligence tool on the overall system performance. A particular fuzzy system for a vehicle dispatching platform involving an automated guided vehicle system (AGVS) will be used for this purpose. With just fuzzy logic alone, the approach to the dispatching of AGVs is based on a self-adapting fuzzy method. This method is provided for a unit load transport system in a manufacturing environment. In this method, it allows for the possibility to formulate more versatile and flexible rules. Thus, the AGVS no longer have to operate in a single criterion satisfaction. The AGVS is able to specialize in a multiple criteria satisfaction. Also, the balance between rules can be precisely adapted to a production environment through real-time parameterization from available information.

The overall effectiveness of this fuzzy logic approach to the vehicle dispatching system for the AGVS is critically dependent on the appropriateness of the fuzzy rules, in particular, the weight or the scaling factors of each of the fuzzy rules on the final dispatch decision. One of the main issues in the fleet control of the AGVS is to address the selection of the scaling factors, i.e., α's as mentioned in Eq. (13.1). The scaling factors could be set based on the experience of the operator and fixed throughout the production process. By this manual adjustment method, the search for the optimal set is by far too tedious and time consuming. Also, an exhaustive search for the optimal set of scaling factors would be unrealistic and impractical. To this end, a systematic search procedure within a balanced set of possible weighting parameters will be both desirable and practical. In this section, the results of using the Taguchi method to tune the fuzzy rules in the fuzzy vehicle dispatching system will be elaborated.

The key idea in the proposed approach is to associate all the work centers in the system with two attributes for each respective vehicle. The two attributes are *PARTS_IN* and *PARTS_OUT*, which are associated with the extent of demand-driven and source-driven needs of the work center with respect to the vehicle (Egbelu and Tanchoco 1984). These attributes are fuzzy variables (i.e., *PARTS_IN*, *PARTS_OUT* $\in$ [0, 1]) computed from a fuzzy operation on a combination of variables which are expected to influence the extent of the demand and source-driven needs of the work center. Decisions for material movement will be driven primarily by these attributes.

The two attributes, *PARTS_IN* and *PARTS_OUT* can be inferred from a Takagi and Sugeno type of fuzzy inference (Haykin 1994). The fuzzy rules will then govern the *PARTS_IN* and *PARTS_OUT* attributes of the work centers. For example from Eq. (13.1), x^i_{kj} may be the linguistic variable *CYCLE_TIME* and F^i_j may be the fuzzy set *SHORT* for the *PARTS_IN* attribute; similarly, x^i_{kj} may be the linguistic variable *WAITING_TIME* and F^i_j may be the fuzzy set *LONG* for the *PARTS_OUT* attribute. The value of the $PARTS\_IN_k$ and $PARTS\_OUT_k$ attributes are then evaluated separately as a weighted average of the u^i's in Eq. (13.2).

With these attributes, the work centers may be sorted in the order of their demand and source-driven needs. In a pull-based situation, an idle vehicle searches for the highest inflow demand station from the *PARTS_IN* attribute. This station may then be paired off with a station having the highest *PARTS_OUT* attribute, identified from a set of K stations supplying the parts to the kth station in demand. The converse is true for a push-based system.

Thus far, dispatching rules are rigidly based on either a demand or a source-driven procedure. There are attractive features associated with a demand-driven rule as they provide the load movement flexibility for just-in-time manufacturing concepts. However, under certain circumstances, it might be more advantageous to revert to a source-driven rule. For example, by reverting to a source-driven rule when there is a low level of demand but a large number of parts to be cleared, machine blockage may be reduced. Furthermore, reverting to the source-driven rule is also a hedge against an unanticipated surge in vehicle demand at a future time.

Instead of rigidly commissioning a push or a pull-based concept, it is viable to view each of these concepts as being suited to different operating conditions, and switch between them when crossing these different operating regions. Clearly, some mechanism to trigger this switch between a pull and a push-based environment is needed. To this end, a methodology may be formulated as follows:

Denote *SCE(k)* as the set of work centers supplying to the input buffer of work center k, and *DES(k)* as the set of work centers to which work center k supplies parts. The work centers, k_u^* and k_v^* are identified where

$$PARTS\_IN_{k_u^*} = max\ (PARTS\_IN_k),\ where\ SCE(k_u^*) \not\subset \emptyset$$
$$PARTS\_OUT_{k_v^*} = max\ (PARTS\_OUT_k),\ where\ DES(k_v^*) \not\subset \emptyset$$

Based on these attributes, the current state system towards a push or a pull operation may be determined. For example, a simple formulation may be to compute the following ratio,

$$STRATEGY = \frac{PARTS\_OUT_{k_v^*}}{PARTS\_IN_{k_u^*} + PARTS\_OUT_{k_v^*}} \tag{13.8}$$

If $STRATEGY > \gamma$ (where suitable values for γ may be in the range $0.6 < \gamma < 0.7$, depending on the desired level of *PULL* dominance), a *PUSH* operation may be initiated, otherwise a *PULL* operation will be initiated. The *PULL* dominance is necessary for reasonably busy facilities where it has been shown (Egbelu and Tanchoco 1984) that a PULL strategy is more efficient in moving parts through the facility.

A graphical representation of the self-adapting fuzzy dispatching algorithm is illustrated in Fig. 13.5. The vehicles are all indexed. When the vehicle in consideration becomes idle, it is available for reassigned to pick up the load from the source work center and then deliver the load to the destination work center. With the idle vehicle in consideration, the fuzzy dispatching algorithm block (as shown in Fig. 13.5) is then invoked. The fuzzy algorithm is represented as an operation block in Fig. 13.5. In Fig. 13.6, the fuzzy algorithm is expanded into further details. Here, the needs of all the work centers are prioritized according to their demand and source driven needs (i.e., the demand and source driven needs are computed using the fuzzy *PARTS_IN* and *PARTS_OUT* attributes). At the end of the execution of the fuzzy dispatching algorithm, the work center (i.e., this work center could either be a source work center or a destination work center; if it is a source work center most in need of service, push-based operation or a source-driven procedure is then selected. If it is a destination work center most in need of service, pull-based operation or a demand-driven procedure is then selected) most in need of service is selected. The vehicle is then invoked to pick up the load from the assigned source work center and then deliver the load to the assigned destination work center. The whole procedure is then repeated for the vehicle, next in the index sequence. If the vehicle next in the sequence is not idle, the fuzzy dispatching algorithm would not be invoked. Instead, it would only continue in its travel to its assigned pick-up work center and then the destination work center.

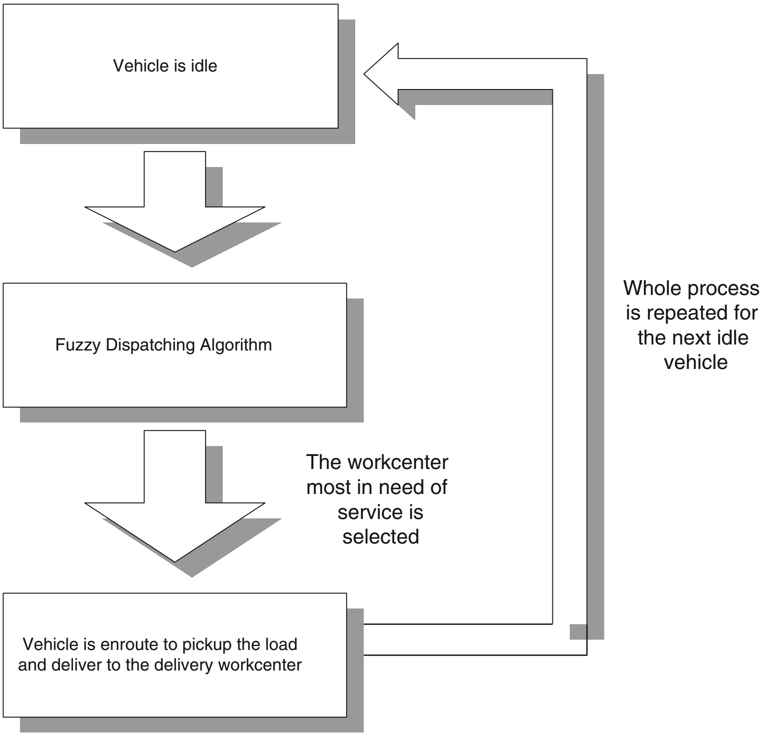


Fig. 13.5 Flowchart of the self-adapting fuzzy dispatching system

While the algorithm is essentially based on vehicle-initiated rules, there are situations such as during start-up, when more than one vehicle is available for dispatching. Since these are insignificant for reasonably busy facilities, a simple random procedure is used to select the vehicle for dispatch under these situations.

13.5.1 Test Facility

The simulation analysis is based on a hypothetical facility as given in Fig. 13.7. The facility operating data is provided in Table 13.1. There are 9 work centers (WC1 to WC9) or departments, and a warehouse (WH) for the raw materials and finished products.

- Job routing = WH, WC1, (WC2, WC3), WC4, WC5, WC6, (WC7, WC8), WC9, WH
- Load pickup/delivery time = 10 s
- Vehicle length = 3 ft.

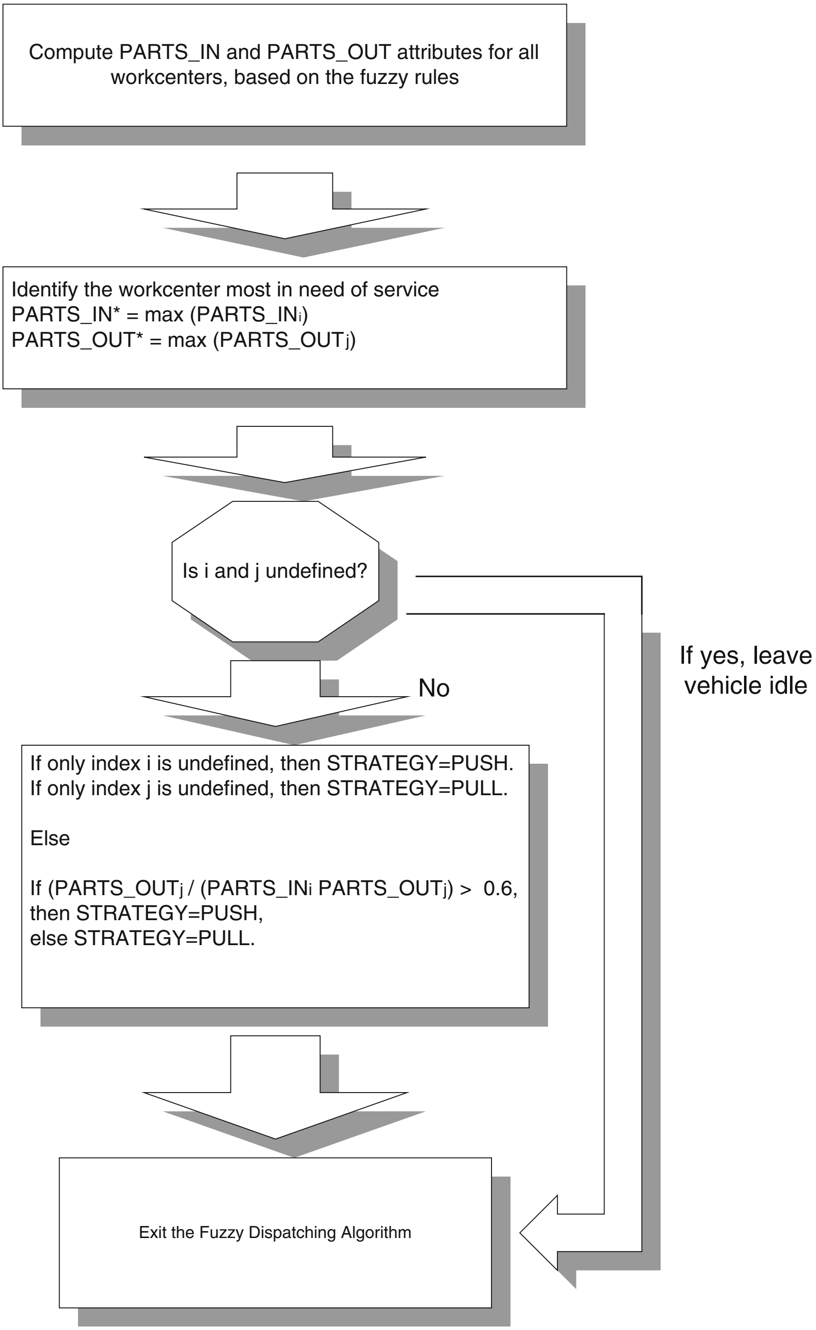


Fig. 13.6 Fuzzy algorithm block (more detailed version)

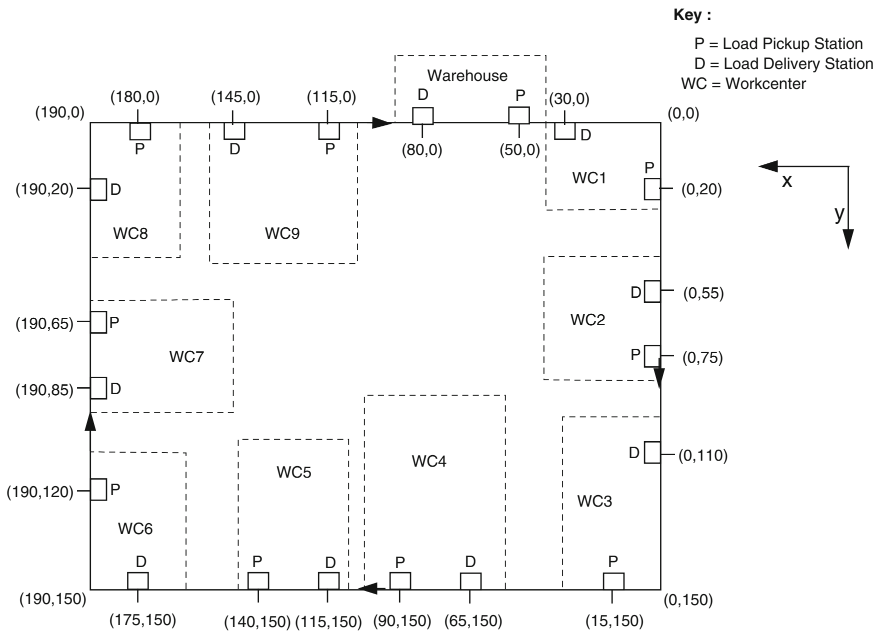


Fig. 13.7 Layout of the test facility

Table 13.1 The test facility operating data

Work center	Processing time/unit load (min)	Input queue size	Output queue size
1	1	3	5
2	3	2	3
3	3	2	3
4	2	3	2
5	1	1	4
6	3	2	3
7	3	2	3
8	2	3	2
9	3	4	4

- Vehicle speed = 200 fpm
- Pickup and delivery spur capacity = 1 vehicle

13.5.2 Simulation Language

The control simulation language, MATLAB is used for implementing the study. The language may be used for simulation of both continuous and discrete-time systems.

In this case, it is applied to discrete event investigation, where the AGV guide path is modeled as a directed network consisting of nodes and arcs. Point locations in the network are uniquely identified by their Cartesian coordinates. Traffic conflicts at the load pickup/delivery points are explicitly modeled.

13.5.3 Computation of Attributes

In this simulation, the input variables chosen for the computation of the *PARTS_IN* attributes are:

- Length of time before incoming queue is empty, **LT_IN**
- Shortest travel distance of vehicle to source work centers, and to the work center concerned, **STD_IN**.
- Shortest length of time before the outgoing queue of source work centers is full, **SLT_IN**
- Number of parts completed already by the workstation, **PC_IN**.

The time taken for the processing of the load at each work center is assumed to be fixed and shown as in Table 13.1 so that these variables can be directly computed. The 4 rules formulated for the computation of the *PARTS_IN* attribute for the *k*th work center are:

IF $\mathbf{LT\_IN_k}$ is SHORT, THEN $u_k = \mu_1$
IF $\mathbf{STD\_IN_k}$ is SHORT, THEN $u_k = \mu_2$
IF $\mathbf{SLT\_IN_k}$ is SHORT, THEN $u_k = \mu_3$
IF $\mathbf{PC\_IN_k}$ is LOW, THEN $u_k = \mu_4$

PARTS_IN is then computed as in (13.2). The input variables chosen for the computation of the *PARTS_OUT* attributes are:

- Shortest length of time before outgoing queue of work center is full, **SLT_OUT**.
- Shortest travel distance of vehicle to work center concerned, and to target work centers, **STD_OUT**.
- Length of time before the incoming queue of destination work center is empty, **LT_OUT**.
- Number of parts completed already by the workstation, **PC_OUT**.

Similarly, the 4 rules formulated for the computation of the *PARTS_OUT* attribute for the *k*th work center are:

IF $\mathbf{SLT\_OUT_k}$ is SHORT, THEN $v_k = \mu_5$
IF $\mathbf{STD\_OUT_k}$ is SHORT, THEN $v_k = \mu_6$
IF $\mathbf{LT\_OUT_k}$ is SHORT, THEN $v_k = \mu_7$
IF $\mathbf{PC\_OUT_k}$ is LOW, THEN $v_k = \mu_8$

PARTS_OUT is then computed as in (13.2). The membership functions are made time varying according to the set of assigned tasks at any point in time. In this approach, a linear interpolation between the maximum and minimum values of the variables serves as the membership function. As an example, consider the following *STD_IN* variable

$$\mu_{SHORT}(STD\_IN_k) = \frac{STD\_IN_k - \min(STD\_IN)}{\max(STD_{IN}) - \min(STD\_IN)} \qquad (13.9)$$

13.5.4 Rule Comparison

The performances of the dispatching system with the deployment of three different deployments will be illustrated. The three different combinations are, just the fuzzy logic alone, the Taguchi-tuned fuzzy system and the demand driven (DEMD) rules of Egbelu (Mandal et al. 2011). The comparisons were carried out under the following three different cases.

Case I Given an equal number of vehicles, the same facility scenario, and the same length of time or shift duration, how does the facility throughput compares between the two sets of rules? Throughput is defined as the total number of parts completed and removed from the facility shop floor during the shift. The following parameters are used for Case I analysis:

- The facility operates a 2-h shift.
- Three vehicles are in use.
- Infinite number of loads were available for processing at time, $t = 0$.

Due to the nature of the dispatching problem, there are a number of quality characteristics that could be considered in the Taguchi-tuned fuzzy system. This quality characteristic is a LTB characteristic.

Case II Given the same conditions as in Case I, how long does it take for the facility to produce a known number of parts under the three different sets of rules? The analysis was done with 3 vehicles and 30 parts or unit loads to be produced and centers on the determination of the length of time it will take the facility to produce the 30 parts under each of the dispatching methodology. The facility operating duration is a measure of the rule's ability to accelerate the unit loads through the facility. In the Taguchi-tuned fuzzy system, this quality characteristic is a STB characteristic.

Case III Given the same conditions as in Case I and a production target over a fixed time period, how many vehicles are required to meet the production target under the three different sets of rules? The conditions for the analysis are the following:

- There are a fixed number (30) of unit loads to be produced.
- The production of the fixed number of unit loads must be satisfied within the time interval specified (2 h).

If all other factors remain the same, it seems that the number of vehicles required will be a function of the dispatching rule (i.e., or control factors in the Taguchi method sense) in force, since the rules act differently with the vehicles. This is a LTB quality characteristic.

13.5.5 Deployment of Taguchi-Tuned Fuzzy System

In the deployment of the Taguchi method to the AGVS, there are some further considerations to modify the problem as a quality optimization problem.

13.5.5.1 Control Factors and Number of Levels

As 4 fuzzy rules are chosen for the *PARTS_IN* fuzzy attribute, there are thus 4 scaling factors (denoted as α_1, α_2, α_3 and α_4) for the *PARTS_IN* fuzzy attribute. Similarly, for the *PARTS_OUT* fuzzy attribute, 4 scaling factors (denoted as β_1, β_2, β_3 and β_4) are selected. These 8 scaling factors for the fuzzy rules are the control factors to be tuned by the Taguchi method for optimal performance. These scaling factors are the parameters as mentioned in Eq. (13.1). The sum of these scaling factors is fixed, i.e., $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$ and $\beta_1 + \beta_2 + \beta_3 + \beta_4 = 1$. This implies that within the set, the factors cannot be varied arbitrarily. But rather the choice of one factor limits the possibilities for the other factors. Due to this constraint, the nested-factor design (Peace 1993) is used for the assignment of the levels of the control factors (shown in Table 13.2). The layout of the first four control factors for the *PARTS_IN* attribute, i.e., α_1, α_2, α_3 and α_4 denoted as *A*, *B*, *C* and *D* respectively, is shown in Table 13.2. The other four scaling parameters for the *PARTS_OUT* attribute, i.e., β_1, β_2, β_3, and β_4 denoted as *E*, *F*, *G* and *H* respectively, have a similar layout as shown in Table 13.2. The factors are scaled up by a factor of 100 for ease of calculations.

Each of the control factors is assigned 3 levels. A 3-layered structure for the control factors is used. Factors *C* and *D* are nested within Factor *B* which is in turn nested within Factor *A*. For example, consider Factor *A* at level 1, i.e., A_1, Factor *B* can be at level 1, level 2 or level 3, i.e., B'_1, B'_2 and B'_3 respectively. For Factor *A* at level 2, i.e., A_2, Factor *B* can be at another set of level 1, level 2 or level 3, i.e., B''_1, B''_2 and B''_3 respectively. The set of levels of Factor *B* at A_1 is different from that at A_2. The same layout is also applied to Factor *B* and Factors *C*, *D*.

As shown in Table 13.3 for Factor *A* (traversing the second column), there are 3 levels, i.e., 1, 50 and 90. Factor *A* at level 1, level 2 and level 3 is denoted as A_1, A_2 and A_3 respectively. For A_1, Factor *B* has three levels: 1, 50 and 90 (denoted as B'_1, B'_2 and B'_3 respectively). For A_2, Factor *B* has another 3 levels: 1, 25 and 40 (denoted as B''_1, B''_2 and B''_3 respectively). For A_3, Factor *B* has another 3 levels: 1, 5 and 9 (denoted as B'''_1, B'''_2 and B'''_3 respectively).

Table 13.2 Layout for the layered structure of the control factors Control factors

Control factors	α_1	α_2	α_3	α_4
Symbol used	*A*	*B*	*C*	*D*
Actual level value	1	1	97	1
			49	49
			1	97
		50	48	1
			24.5	24.5
			1	48
		90	8	1
			4.5	4.5
			1	8
Actual level value	50	1	48	1
			24.5	24.5
			1	48
		25	24	1
			12.5	12.5
			1	24
		40	9	1
			5	5
			1	9
Actual level value	90	1	8	1
			4.5	4.5
			1	8
		5	4	1
			2.5	2.5
			1	4
		9	0.9	0.1
			0.5	0.5
			0.1	0.9

Table 13.3 Optimum levels of the various control factors Control factors

Control factor	Optimum level	Value
A	A_1	0.01
B	B'_1	0.01
C	$(CD)_1^{\prime 1}$	0.49
D	$(CD)_2^{\prime 1}$	0.49
E	E_1	0.01
F	F'_3	0.90
G	$(GH)_1^{\prime 3}$	0.08
H	$(GH)_1^{\prime 3}$	0.01

13.5.5.2 Orthogonal Array and Linear Graph

For this vehicle dispatching problem considered here, the required DOF is 36, obtained as follows.

Axial factor (*A*)	1 × (3 − 1) = 2 DOF
Nested factor (*B*)	1 × (3 − 1) = 2 DOF
Nested factor (*C* & *D*)	1 × (3 − 1) = 2 DOF
Axial nesting for *A* & *B*	1 × (3 − 1) (3 − 1) = 4 DOF
Axial nesting for *A* & *B* & *C*, *D*	1 × (3 − 1) (3 − 1) (3 − 1) = 8 DOF
Total DOF needed for *A*, *B*, *C*, *D* = 18	
Total DOF needed for *A*, *B*, *C*, *D* & *E*, *F*, *G*, *H* = 36	

The L_{81} (3^{40}) orthogonal array (Peace 1993) is used, being the smallest array with a degree of freedom larger than 36. The subscript refers to the number of experiments or rows in the array whereas the superscript refers to the number of factors or columns in the array. For this array, there are many different linear graphs with different structures (Peace 1993). The linear graph chosen is as shown in Fig. 13.8. The nodes represent the control factors. The joining arcs represent the interactions or the relationship between the control factors. The numbers in brackets refer to the column number in which the particular control factor is assigned to in the orthogonal array.

13.5.5.3 Results of the Experiments

After the experiments are run, the optimum condition is determined by selecting the best levels of each factor. Note that the choice of one factor limits the choice of subsequent ones due to nesting. The average level of a factor is obtained by summing the experimental data for each particular level of a factor and averaging the sum by the number of experiments. The best level of a factor is the level with the highest average level (for a LTB quality characteristic) or the level with the

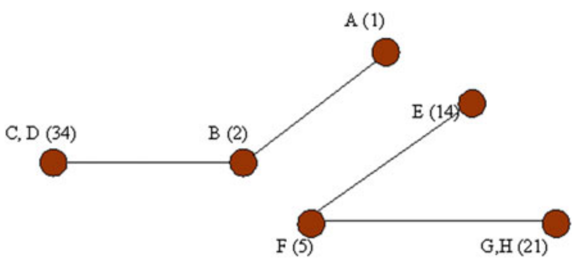


Fig. 13.8 Linear graph for the control factors in the L_{81} (3^{40}) orthogonal array

lowest average level (for a STB quality characteristic). The best levels for the factors are thus obtained as illustrated from Fig. 13.9 to 13.14.

In this experiment, the quality characteristic of concern is a LTB quality characteristic. From the factors' effects plot above (Figs. 13.9, 13.10, 13.11, 13.12, 13.13 and 13.14), the optimum condition is thus obtained by choosing the factors combination A_1, B_1' and $(CD)_1^{\prime 1}, E_1, F_3'$ and $GH_1^{\prime 3}$. The next best factors combination is A_1, B_1' and $(CD)_2^{\prime 1}, E_1, F_3'$ and $GH_1^{\prime 3}$. There is little difference between Factor $(CD)_1^{\prime 1}$ and $(CD)_2^{\prime 1}$ on the quality characteristic. Using the two optimum sets of factors, a final test run is done. The results of the final test run confirm that the optimum condition obtained for the control factors at the given levels as shown in Table 13.3.

Here, Factor A at Level 1, Factor B at Level 1 and Factors C and D at Level 2 are chosen, whereas Factor E at Level 1, Factor F at Level 3, and Factors G and H at Level 1 are chosen.

13.5.5.4 Validation with Statistical Tools

As mentioned at the start of this chapter, after the experimental data from the set of weighting parameters is obtained, the statistical tools could be used to interpret the experimental data mathematically and to provide indications of whether the choice is adequate and if further experimentation is necessary. For this purpose in this chapter, the analysis of variance (ANOVA) is chosen. This is because when results of laboratories or methods are compared where more than one factor can be of influence and must be distinguished from random effects, then the ANOVA is a powerful statistical tool to be used. Furthermore, the ANOVA also allows one to assess the degree to which a factor affects variation and the quality characteristic. ANOVA is used as a supplement to the experimental design (Sreenivasulu 2013; Asafa and Said 2013; Mandal et al. 2011; Tzeng et al. 2009; Howanitz and Howanitz 1987; International Organization for Standardization 1981; Bauer 1971).

Analysis results from the ANOVA method are summarized in Table 13.4. The results obtained by the ANOVA method confirm the results obtained earlier. Referring to Table 13.4, the second column (F) refers to the degrees of freedom of each factor. The third column (S) refers to the factor variation and error variation. The fourth column (V) refers to the factor variances and the error variance. The fifth

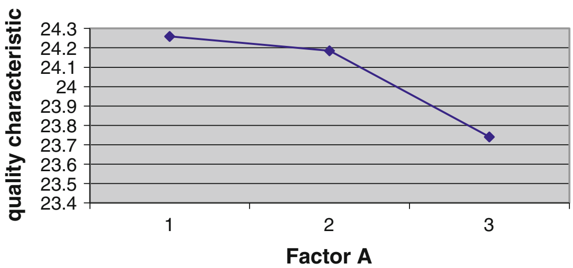


Fig. 13.9 Factor effects of Factor A

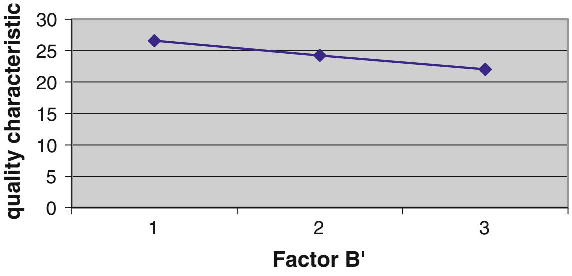


Fig. 13.10 Factor effects of Factor B'

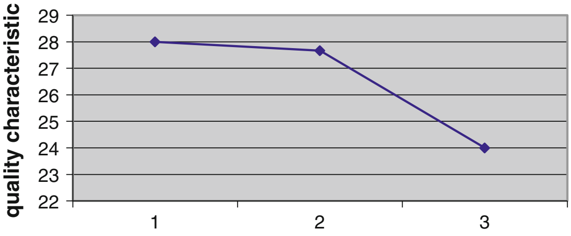


Fig. 13.11 Factor effects of Factor CD'^{1}

Fig. 13.12 Factor effects of Factor E

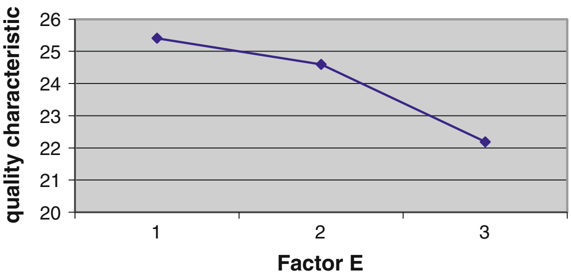
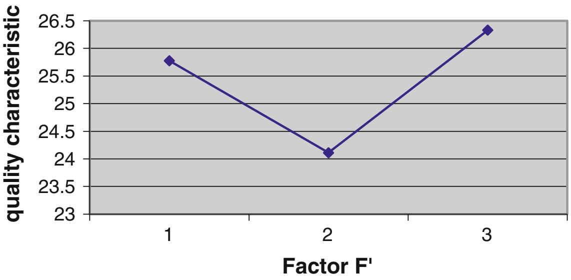


Fig. 13.13 Factor effects of Factor F'



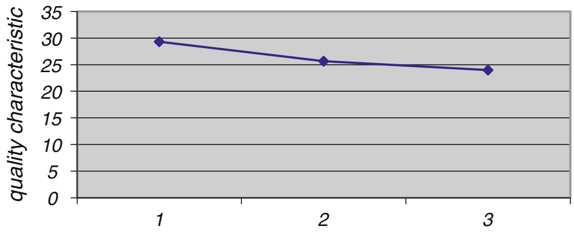


Fig. 13.14 Factor effects of Factor GH'^3

column (F) refers to the variance ratio of each the factor variance to the error variance. The last column (ρ) refers to the contribution ratio, i.e., significance or importance with regards to the particular quality characteristic, of each factor.

There are two conclusions that can be drawn from the ANOVA table to support the optimum combination of factors obtained earlier. First, there is about 11 % of significance to the quality characteristic due to uncontrolled or unwanted factors. This implies positively that the factors chosen earlier to study their effects on the quality characteristic has a major influence of about 89 % on the quality characteristic. Secondly, the factors chosen earlier in Table 13.3 are indeed those with most significant contribution to the quality characteristic, as shown in the last column of Table 13.4 by their contribution ratio. Referring to the contribution ratio (last column of Table 13.4), Factor A has a significance of about 0.259 % on the quality characteristic. From the factor effects graph of Factor A (Fig. 13.9), Level 1 is chosen as the optimum level. For Factors B', B'' and B''', B' with Level 1 is chosen in the optimum factor combination from the factor effects' graph as A_1 is chosen. This is due to the nesting arrangement in Table 13.2. Factor B' has the highest contribution ratio among B', B'' and B'''. For Factor CD, the optimum factor chosen from the factor effects' graph is $(CD)'^1$. This is again due to the nesting arrangement in Table 13.2 as we have chosen A_1 and B'_1. Factors $(CD)'^1$, $(CD)'^2$ and $(CD)'^3$ have quite similar contribution ratios.

13.5.6 Simulation Results

The values of the manually adjusted (in a trial-and-error manner) scaling factors (i.e., α's as mentioned in Eq. (13.1)) obtained manually by trial and error method, are shown in Table 13.5. For this approach, the scaling parameters are changed on a rather ad hoc basis, relying solely on the experience and the judgment of the operator. For the Taguchi method, the obtained weighting parameters at the end of the tuning procedure are given in the third row of Table 13.5.

Based on the scaling factors in Table 13.5, the performances of the various dispatching methods are compared and summarized in Table 13.6. It can be seen that the Taguchi-tuned fuzzy dispatching methodology has outperformed the

Table 13.4 Table showing the ANOVA results

Factor	F	S	V	F	ρ %
A	2	4.247	2.123	2.279	***0.259***
B'	2	93.407	46.704	100.298	***9.950***
B''	2	23.407	11.704	25.134	2.340
B'''	2	3.185	–	–	–
CD'^{1}	2	29.556	14.778	31.736	***3.008***
CD'^{2}	2	29.556	14.778	31.736	3.008
CD'^{3}	2	52.667	26.334	56.552	5.519
CD''^{1}	2	24.889	12.445	26.725	2.501
CD''^{2}	2	4.222	2.111	4.553	0.256
CD''^{3}	2	10.889	5.445	11.692	0.980
CD'''^{1}	2	2.889	–	–	–
CD'''^{2}	2	2.889	–	–	–
CD'''^{3}	2	3.556	–	–	–
E	2	151.580	75.790	162.762	***16.261***
F'	2	24.074	12.037	25.850	2.412
F''	2	18.074	9.037	19.407	1.761
F'''	2	10.296	5.148	11.056	***0.916***
GH'^{1}	2	94.889	47.445	101.056	***10.104***
GH'^{2}	2	81.556	40.778	87.573	8.656
GH'^{3}	2	44.667	22.334	47.962	4.649
GH''^{1}	2	82.889	41.445	89.004	8.801
GH''^{2}	2	28.667	14.334	30.782	2.911
GH''^{3}	2	0.222	–	–	–
GH'''^{1}	2	24.667	12.334	26.487	2.477
GH'''^{2}	2	0.222	–	–	–
GH'''^{3}	2	26.889	13.445	28.873	2.718
Total	80	920.691	–	–	100
Error	64	59.603	0.932	1	10.513

Table 13.5 Values of the scaling factors for the different approaches

Scaling factors	α_1	α_2	α_3	α_4	β_1	β_2	β_3	β_4
Trial and error setting	0.1	0.5	0.2	0.2	0.2	0.5	0.1	0.2
Taguchi method	0.01	0.01	0.49	0.49	0.01	0.50	0.48	0.01

manually tuned fuzzy dispatching rules of and DEMD dispatching rules of Egbelu for all the three cases studied. It is also interesting to note the improvement of the performance of the system with the introduction of fuzzy logic to this vehicle dispatching platform.

Table 13.6 Rule comparisons of the various methods

	DEMD (Egbelu)	Fuzzy	% Improvement (Fuzzy vs. DEMD) (%)	Taguchi-tuned Fuzzy	% Improvement (Taguchi-Fuzzy vs. Fuzzy) (%)
Case I: Throughput	16	27	69	31	14.81
Case II: Production time/h	2.99	2.14	28	1.95	19.74
Case III: No of vehicles	9	5	44	3	40

The results in this study concur with the other works in the literature that integrate the Taguchi method with other tools in artificial intelligence (i.e., genetic algorithm, neural networks, fuzzy logic and regression analysis) to optimize processes and systems (Lin et al. 2012; Sun et al. 2012; Mandal et al. 2011; Chang 2011; Tsai 2011; Tansel et al. 2011; Tzeng et al. 2009). The integrated approach of the Taguchi method with other artificial intelligence tools produces better results than just utilizing a single optimization tool alone. For this study, it is also interesting to note that there is a marked improvement in the fuzzy system for the third case. It is to be noted that the Taguchi method performs well when the boundaries of the search space is well-defined. With the production time and other manufacturing constraints fixed, the Taguchi method seeks to only optimize the vehicles deployed.

13.6 Conclusions

Since Dr. Genichi Taguchi introduced the Taguchi method as a practical statistical tool in the 1980s to improve the quality of manufactured goods, there has been increasing interests on the Taguchi method in various industries and the academia. It is to be noted that in the literature, there is a strong focus on the application and verification of the Taguchi method. Recently, there are several works in the literature that integrate the Taguchi method with other tools in artificial intelligence (i.e., genetic algorithm, neural networks, fuzzy logic and regression analysis) to optimize processes and systems. This is interesting in that the main strengths of the Taguchi methods are accentuated with a well-defined boundary for a given search space. The results in the literature show that the integrated approach of the Taguchi method with other artificial intelligence tools produce better results than just utilizing a single optimization tool alone. Besides modeling and optimizing manufacturing processes, the Taguchi method has also been widely applied in other non-conventional fields.

In this chapter, a few possible approaches of integrating the Taguchi method combined with some artificial intelligent techniques, to create hybrid approaches with improved overall system performance, are elaborated. Particularly, details and illustrations of combining the Taguchi method with a fuzzy system and a radial basis neural network are provided. In the simulation study, the adaptive fuzzy rules are formulated to base the decision making process and the Taguchi method is applied to fine tune the rules for optimal performance. The experimental design is performed and simulations are conducted to compare the Taguchi-tuned fuzzy method to other earlier reported methods. The results in this study concur with the other works in the literature that integrate the Taguchi method with other tools in artificial intelligence.

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References

Asafa, T.B., Said, S.A.M.: Taguchi method–ANN integration for predictive model of intrinsic stress in hydrogenated amorphous silicon film deposited by plasma enhanced chemical vapour deposition. Neurocomputing **106**, 86–94 (2013)

Bauer, E.L.: A Statistical Manual for Chemists. Academic Press, New York (1971)

Chang, K.Y.: The optimal design for PEMFC modeling based on Taguchi method and genetic algorithm neural networks. Int. J. Hydrogen Energy **36**, 13683–13694 (2011)

Chen, Y.H., Tam, S.C., Chen, W.L., Zheng, H.Y.: Application of Taguchi method in the optimization of laser micro-engraving of photomasks. Int. J. Mater. Prod. Technol. **11**, 333–344 (1996)

Chou, J.H., Chen, S.H., Li, J.J.: Application of the Taguchi-genetic method to design an optimal grey-fuzzy controller of a constant turning force system. J. Mater. Process. Technol. **105**, 333–343 (2000)

De Souza, H.J.C., Moyses, C.B., Pontes, F.J., Duarte, R.N., Da Silva, C.E.S., Alberto, F.L., Ferreira, U.R., Silva, M.B.: Molecular assay optimized by Taguchi experimental design method for venous thrombo-embolism investigation. Mol. Cell. Probes **25**(5), 231–237 (2011)

Ealey, L.A.: Quality by Design. Irwin Professional Publishing, Illinois (1994)

Egbelu, P.J.: Pull versus push strategy for automated guided vehicle load movement in a batch manufacturing system. J. Manuf. Syst. **6**, 209–221 (1987)

Egbelu, P.J., Tanchoco, J.M.A.: Characterisation of automated guided vehicle dispatching rules. Int. J. Prod. Res. **22**, 359–374 (1984)

Haykin, S.: Neural Networks—A Comprehensive Foundation. MacMillan Publishing Company, New York (1994)

Hissel, D., Maussion, P., Faucher, J.: On evaluating robustness of fuzzy logic controllers through Taguchi methodology. In: Proceedings of the IEEE Industrial Electronics Society 24th Annual Conference, IECON'98, pp. 17–22 (1998)

Ho, W.H., Tsai, J.T., Chou, J.H.: Robust-stable and quadratic-optimal control for TS-fuzzy-model-based control systems with elemental parametric uncertainties. IET Control Theory Appl. **1**, 731–742 (2007)

Hoa, W.H., Tsai, J.T., Lin, B.T., Chou, J.H.: Adaptive network-based fuzzy inference system for prediction of surface roughness in end milling process using hybrid Taguchi-genetic learning algorithm. Expert Syst. Appl. **36**, 3216–3222 (2009)

Hong, C.W.: Using the Taguchi method for effective market segmentation. Expert Syst. Appl. **39**, 5451–5459 (2012)

Howanitz, P.J., Howanitz, J.H.: Laboratory quality assurance. McGraw-Hill, New York (1987)

Huang, S., Tan, K.K., Tang, K.Z.: Neural Network Control—Theory and Applications. Research Studies Press, London (2004)

Hwang, C.C., Chang, C.M., Liu, C.T.: A fuzzy-based Taguchi method for multiobjective design of PM motors. IEEE Trans. Magn. **49**, 2153–2156 (2013)

International Organization for Standardization: Statistical methods. ISO Standards Handbook 3, 2nd edn. ISO Central Seer., Genève (1981)

Khaw, F.C., Lim, B.S., Lim, E.N.: Optimal design of neural networks using the Taguchi method. Neurocomputing **7**, 225–245 (1995)

Lin, H.C., Su, C.T., Wang, C.C., Chang, B.H., Juang, R.C.: Parameter optimization of continuous sputtering process based on Taguchi methods, neural networks, desirability function, and genetic algorithms. Expert Syst. Appl. **39**(17), 12918–12925 (2012)

Mandal, N., Doloi, B., Mondal, B., Das, R.: Optimization of flank wear using Zirconia Toughened Alumina (ZTA) cutting tool: Taguchi method and regression analysis. Measurement **44**(10), 2149–2155 (2011)

Mori, T.: The New Experimental Design. American Supplier Institute, Michigan (1993)

Peace, G.S.: Taguchi Methods. Addison-Wesley Publishing Company, New York (1993)

Rao, R.S., Kumar, C.G., Prakasham, R.S., Hobbs, P.J.: The Taguchi methodology as a statistical tool for biotechnological applications—a critical appraisal. Biotechnol. J. **3**, 510–523 (2008)

Ross, J.R.: Taguchi Techniques for Quality Engineering. McGraw-Hill, Columbus (1988)

Sreenivasulu, R.: Optimization of surface roughness and delamination damage of GFRP composite material in end milling using Taguchi design method and artificial neural network. Procedia Eng. **64**, 785–794 (2013)

Sun, J.H., Fang, Y.C., Hsueh, B.R.: Combining Taguchi with fuzzy method on extended optimal design of miniature zoom optics with liquid lens. Optik—Int. J. Light Electr. Opt. **123**(19), 1768–1774 (2012)

Taguchi, G., Yokoyama, T.: Taguchi Methods—Design of Experiments. Dearborn, ASI Press, Tokyo (1993)

Taguchi, G., Chowdhury, S., Wu, Y.: Taguchi's Quality Engineering Handbook. Wiley, Hoboken (2004)

Takagi, T., Sugeno, M.: Fuzzy identification of systems and its applications to modelling and control. IEEE Trans. Syst. Man Cybern. **15**, 116–132 (1985)

Tan, K.K., Tang, K.Z.: Taguchi-tuned radial basis function with application to high precision motion control. Artif. Intell. Eng. **15**, 25–36 (2001)

Tansel, I.N., Gülmez, S., Aykut, S.: Taguchi Method–GONNS integration: complete procedure covering from experimental design to complex optimization. Expert Syst. Appl. **38**(5), 4780–4789 (2011)

Tortum, A., Yaylab, N., Celikc, C., Gökdag, M.: The investigation of model selection criteria in artificial neural networks by the Taguchi method. Phys. A **386**, 446–468 (2007)

Tsai, T.N.: Improving the Fine-Pitch Stencil printing capability using the Taguchi method and Taguchi fuzzy-based model. Robot. Comput.-Integr. Manuf. **27**, 808–817 (2011)

Tzeng, C.J., Lin, Y.H., Yang, Y.K., Jeng, M.C.: Optimization of turning operations with multiple performance characteristics using the Taguchi method and grey relational analysis. J. Mater. Process. Technol. **209**(6), 2753–2759 (2009)

Wang, J.L., Wan, W.: Experimental design methods for fermentative hydrogen production. Int. J. Hydrogen Energy **34**(1), 235–244 (2009)

Woodall, W.H., Koudelik, R., Tsui, K.L., Kim, S.B., Stoumbos, G., Carvounis, C.P., Jugulum, R., Taguchi, G., Taguchi, S., Wilkins, J.O., Abraham, B., Variyath, A.M., Hawkins, D.M.: Review and analysis of the Mahalanobis-Taguchi system. Technometrics **45**, 1–30 (2003)

Yang, T., Wen, Y.F., Wang, F.F.: Evaluation of robustness of supply chain information-sharing strategies using a hybrid Taguchi and multiple criteria decision-making method. Int. J. Prod. Econ. **134**(2), 458–466 (2011)

Yu, G.R., Huang, J.W. Chen, Y.H.: Optimal fuzzy control of piezoelectric systems based on hybird Taguchi method and particle swarm optimization. In: Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics, pp. 2794–2799. IEEE Press (2009)

Zadeh, L.A.: Outline of a new approach to the analysis of complex systems and decision process. IEEE Trans. Syst. Man Cybern. **3**, 28–44 (1973)

Zurada, J.M.: Introduction to Artificial Neural Systems. West Publishing Company, New York (1992)