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A Primary Robustness Optimization Strategy of Multi-Item and Low-Volume Process*

Jianguo CHE

Department of Industry Engineering, Nankai University, Tianjin, China.
Email: cjg7705@yahoo.com.cn

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ABSTRACT

Multi-item and low-volume process is a production system with multi-input source, interactions between input variables, and frequently changes of system state, etc. Strong interactions between input variables and time-varying of input variables cause poor robustness and large variation range of output quality, which produces high cost, heavy waste and low efficiency of multi-item and low-volume process. Robustness optimization of multi-item and low-volume process is a new, important and need-to-deep research field with multi-item and low-volume production system prevails. It proposed a strategy enhancing robustness of multi-item and low-volume process by Taguchi robust design. Firstly, build and analyze a fitting output response model of multi-item and low-volume process after taking the adjustable variables (or time-varying variables) corresponding to each item and interaction between input variables into fitting output response model of multi-item and low-volume process as input variables uniformly, and treating the parameter value of time-varying variables corresponding to each item as level value of the adjustable variables (or signal factors) of process. Secondly, present robustness evaluation index based on evidential theory, desirability function and dual response surface etc. Finally, choose the proper experiment type and optimize the process. And then the robustness optimization of multi-item and low-volume process can be reached.

Keywords: *multi-item and low-volume process, robustness optimization, robust design, time-varying, interaction*

1. Question Presenting

The mass production system cannot meet customer's demand on product's quality, item, price and delivery time for rigescent, low-efficient and laggard resource allocation system. Multi-item and low-volume production system becomes popular with the increasing customer's diversified, individual demand.

In multi-item and low-volume process (MILV process), there exist followed questions as:

1) There are various production items, materials and complicated process routes in MILV process, and the process is affected by man, machine, material, method of operation, measurement, environment and other influence factors (5M1E factors), which bring quality fluctuation of process output, so multi-variation of MILV process is a key problem.

2) Usually for MILV process, the parameter values of input variables（or factors） have to be renewed (such as replacing material, adjusting the level values of process variables, etc.) with one item being shifted, which brought time-varying of MILV process (here we called the adjustable influence factors time-varying variables).

Normally, even if MILV process is in control, due to low volume of each item and frequent change of production boundary and system state, the production process can have been completed while the process didn't get stabilization, which leads to unstable output quality. So time-varying is the second key problem of MILV process.

3) The process is affected by the 5M1E factors, and there exist interactions between the factors. When one item has been shifted to another, the interaction will change with this process state alters, which brings output quality of next item unsteady and hard-to-control, and increases source and range of variation. So interaction between input variables of MILV process is third key problem.

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From the view of system, MILV process is a typical production system with multi-input source, multi-stage, multi-response, time-varying, and strong interaction between input source variables of the process. Multi-variation, time-varying and strong interaction bring badly robustness of the process, and increases variation of the process and cost of poor quality of the firm.

Since the premise of monitoring the process with the Shewhart control chart is steady-state stochastic process, sufficient process capability, adequate and independent identically distributed process data, and if MILV process cannot meet these conditions, to monitor MILV process with control chart will lead to heavy false alarms and missing alarms, and greatly cut down the average run length of in-control process. To some extent, MILV process cannot reach indeed in-control state, and due to quality control is a non-value added activity and passively adaptive quality policy. Simple quality control of MILV process is not only difficult but less significant.

Robustness optimization is a systemic method to enhance output quality of MILV process, which can systemically prevent and reduce out-of-control and output quality fluctuation of process.

Robustness optimization of MILV process is more complicated and significant than that of mass production process. Now MILV process is mostly applied to vehicle, machine and electronic industries and so on. Study on robustness optimization of MILV process can not only improve output efficiency and quality of process and reduce waste and production cost of the firm, but have an important theoretical significance and application value.

2. Literature Reviews

The principle of robustness optimization is early presented by the Japan scholar Dr. Genichi Taguchi, and it is widely recognized and employed for its advantage improving product quality [1].

Taguchi parameter design better enables a product or process to perform consistently as intend over a wide range of operating conditions. The primary principle of Taguchi parameter design with dynamic output characteristics is to find an optimal level combination of control factors (i.e. controllable influence factors of process) which makes the output response of the production process insensitive to variation of noise factors and sensitive to variation of signal factors (i.e. variation of the adjustable influence factors or time-varying input variables of the process). Systematic changing of the combination and levels of control factors, consistent with the nonlinear relationships between those control factors and output response and the linear relationships between the signal factors and output response, leads to more robust designs [1,2].

A graphical presentation of the concept is shown in the Figure 1. The output response has a nonlinear relationship with control factor C, and a linear relationship with control factor T. The target value of the output response Y (i.e. critical to quality) of the process when factor C is located at level C_1 and signal factor is given to a certain value is labeled Y_1. At this point, a small fluctuation ΔC around C_1 would cause a relatively large oscillation ΔY_1 of Y, which makes output quality of the process highly unstable. When control factor C has a value of C_2, the output response value is shown as Y_2. A control factor fluctuation of the same magnitude (i.e. ΔC) produces a less-pronounced oscillation of Y, shown as ΔY_2. The goal of Taguchi parameter design with robustness (also called Taguchi robust design) is to find a level combination of influence factors with the strongest anti-interference ability through design of experiment and analysis of data, which will minimize fluctuation of the output response Y, and then to adjust value of the output response Y_2 to the original target output Y_1 by changing the level of the linear influence factor T (also called signal factor or time-varying input variables of the process) from T_2 to T_1.

For the study of robustness optimization, the measurement of process robustness is an important issue, and signal to noise ratio (SN ratio) is early introduced by Dr. Taguchi to define the robustness of production system. Many criticisms are got to SN ratio for lack of mathematical logic fundamental, and Reference [2] pointed out that SN ratio was low efficient for losing more than seventy percent data of process. In 1987, Leon, Shoemaker and Kacker introduced Performance Measure Independent of Adjustment (PerMIA) by studying SN ratio, and proved SN ratio was a PerMIA [3]. Reference [4] found that most criticisms on Taguchi method were focused on use of SN ratio by examining the viewpoints in the field of robust design. Since SN ratio didn't tell from control factors' influence on mean and variance, other people also tried to build and analyze the models of critical-to-quality's mean and variance respectively. And many people presented many indexes measuring the robustness of process respectively [5], such as extension of SN ratio, standard deviation or variance of output response characteristics, vibration range of output response characteristics or the ratio of vibration range to expectation of output response characteristics [6], rejection rate

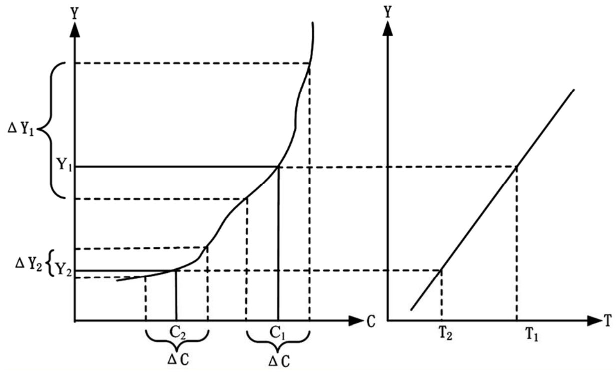

Figure 1. Nonlinear effect of Taguchi robust design

or yield rate, Information Entropy of process quality [7], etc.

At present methods of robustness optimization can be cut into two catalogs [5]: one is traditional method of robustness optimization based on experiential or semi-experiential design, such as Taguchi robust design, design of experiment, response surface methodology etc. Without getting process model, these methods find the optimal parameter values of process through experiments and explorations. Due to just considering single output response characteristic problem with finite-level influence factors, optimization methods of this catalog are difficult to fit second-order and above response surface model, and these methods hardly get the global optimal solution for the finite changing range and amount of parameters, they can be only adapted to the design with mono-response, few variables and no constraint condition. Another catalog is what calls engineering robustness or analytic robustness, to get the optimal parameter values of process by computing engineering model with optimization technology, including generalized linear model, tolerance polyhedron, propagation of Error, state space method, sensitivity analysis, stochastic model, and hybrid robust design based on cost and quality model etc [8]. These methods have a limited application scope due to complicate solution process and requirement of exact output quality model in advance.

Reference [5] pointed out, robustness optimization, the combination of robust design and optimization design, enables the robustness of process optimal solution by adjusting the nominal value of process variables and controlling the variation of variables. That is, robustness optimization makes output response characteristics low sensitive to the variations of process, and seeks the optimal feasible solution of robust design in the meanwhile.

References [8,9] also divided the engineering model into two catalogs: feasible robustness and sensitive robustness. He discussed seven robust design methods of engineering model, and indicated that robust design is an optimization problem, which is the kernel idea that the fluctuation of design parameters leads to the variation of the goals and constraint conditions, and the optimization problem is addressed by the quantitative design with the goal minimizing the variation.

Reference [10] considered that robust design minimized the variation of noise factors and control factors, to improve product quality, instead of removing source of variation. He also divided robust design into two catalogs: one is to minimize the influence of noise factors' variation on systemic performance, and another is to minimize the influence of control factors' variation on systemic performance. And he indicated that Taguchi design comes from the previous one, and the solution process of two problems included three followed steps as: 1) to establish the output response model involved all the primary control factors and noise factors by response surface methodology. 2) to build the mean and variance function according to the type of robust design problem respectively. 3) to solve robust design problem with compromise decision support method, etc.

Reference [11] considered that choosing proper variables to minimize the quality sensitivity to the uncertain factors can get process robustness in robust design, which advantage is to design the low-cost product accepting larger tolerance.

Response surface methodology, presented by Box and Wilson, is the statistics technology modeling and analyzing multivariate problem based on design of experiment. Earlier response surface methodology didn't consider noise factors, and in 1980 Myers and Montgomery [12] introduced noise factors to build respectively mean and variance fitting response models, and then robust design based on response surface methodology is presented.

Reference [13] said that response surface methodology, consisting of selection of parameters, local optimization and global optimization, can be applied to robust parameter design. And the kennels of response surface methodology are: 1) to take output response of process as linear function of control factors, noise factors and their interactions and build the function. 2) to select the proper response surface design type, carry on the experiments and get the experimental results of output response. 3) to estimate results of parameter of linear model with least square method. 4) to define the significant factors and interactions with semi-normal distribution plot (or analysis of variation, step regression, Cp statistics, etc), and then get an estimation and explanation of the factors with engineering analysis.

Now two methods of robust design based on response surface methodology is brought as followed: one is to establish mean and variance fitting models involved the design variables (or control factors) respectively, which is usually called dual response surface methodology. Another is to establish response surface model involved control factors and noise factors by experiments, and the output response model of mean and variance is presented based on Lucas's propagation of error [14].

Dual response surface methodology is a robustness optimization method building mean and variance fitting response model respectively by design of experiments and optimizing the model as a minimized constraints problem. There are the advantages that strict mathematical logic fundamental, consideration of error distributions and interactions between influence factors, more accurate solutions, higher optimization efficiency, higher reliability and robustness and the disadvantages that obtaining some key parameters by experience can bring repeated experiments and calculations when building the response model for dual response surface methodology. Again, to fit model will be highly complicated and difficult if interference variables or some High-dimensional variables are involved in dual response surface model [15].

The problems often arose in engineering optimization are as followed: 1) random factors' influence to quality fluctuation. 2) The nonlinear implicit function relations between design variables and response do not make for optimization. 3) Continuous correction of design variables in optimization evidently increases experimental or computational cost. For above problems, Reference [16] introduced the six sigma robustness optimization method by combining six sigma and dual response surface methodology and illustrated with drawing and shaping case of the ancon and tube-shape piece.

3. Robustness Optimization Strategy of MILV Process

Robustness optimization of MILV process is a new, important and need-to-deep research field. We had a work on quality improvement of MILV process with Taguchi robust design, but due to a nonlinear function relation or implicit function relation between input variables and output response variable exist in MILV process, which cannot meet the requirement of a linear function relationship for Taguchi robust design, and Taguchi robust design cannot manage the strong interaction between input variables and output response variable, and time-varying variable problem, which only applies Taguchi design in some specific MILV processes, and greatly narrowed the applicable field of Taguchi robust design. Furthermore, the robustness evaluation index of Taguchi design SN ratio cannot tell the contribution of high SN ratio from output response mean or variance, etc, which leads to many criticisms, and due to there are different output target value and error requirement for each different item of MILV process, and therefore there are no comparability of SN ratio between different items, so we have to find a revised Taguchi design method or other methods to improve robustness of MILV process.

Generally, robustness design of MILV process need to solve two primary problems followed: one is to build fitting model of MILV process, another is to introduce the robustness evaluation index of MILV process. And we can realize the robustness optimization of MILV process by design of experiment after solving two problems.

For the above problems, we believe that the interaction and time-varying between/of input variables causes the poor robustness of MILV process. Since the identical modal of time-varying variables, we can take the followed steps to obtain the robustness of MILV process as: 1) to treat time-varying variables and other input variables as input variables of MILV process uniformly, and take the interaction between input variables into MILV process model, and then establish MILV process fitting output response model involved input variables, the interactions between input variables and output response variables. 2) to present robustness evaluation index of MILV process. 3) according to the idea of Taguchi robust design with dynamic output characteristics, take time-varying variables as input signal factors of MILV process model, and take time-varying variable value corresponding to each item and output response mean of each item as the corresponding level of input signal factor and the corresponding parameter level of output response variable of MILV process respectively, and then design and optimize the robustness experiments. 4) the fitting surface model of MILV process can be got by solution and optimization of the model, and MILV process robustness optimization with time-varying variables and interactions between the input variables.

In robustness optimization of MILV process, it is very important and difficult to propose robustness optimization index of MILV process. And then we will try to propose the index based on evidential theory, desirability function and dual response surface and other methods.

Furthermore, since Taguchi design with the inter-outer array structure is difficult to solve the interactions between design variables in design of experiment, we have to select other design type of experiments according to the interactions. And in general, if we consider all the interactions of input variables adequately, the best one is full factorial design. But full factorial design will cause high number and cost of experiments if there are many input variables of MILV process, we have to choose few variables for full factorial design. Since not all the inter-actions between the input variables exist, and usually we can know the variables between which the interactions exists in advance, we can choose the proper design such as Taguchi design, response surface methodology etc, and then take the factors between which interaction exists in the specific array to estimate the interactions, or we can choose fractional factorial design with small experiment number to optimize the MILV process. Furthermore, if we cannot know the interactions between all the factors, we can estimate the known interactions, and analyze the goodness-of-fit of fitting model, and then do the experiments until the satisfactory goodness-of-fit of fitting model is obtained.

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