The E.M. Method, a new tool to reduce non-quality losses in the manufacturing industry

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Improving quality, reducing costs and shortening development times are universal objectives for the manufacturing industry. Many statistical tools have been developed to achieve such objectives. Experimental design methods are especially useful for :

- designing and improving products;
- developing new processes;
- characterizing and optimizing manufacturing processes.

These methods are used at the laboratory level, at the pilot plant level, and more problematically, at the shop-floor level.

The product or the process is modeled as a "black box" with a set of inputs and outputs. The inputs are controllable factors such as feed rate, speed, temperature and uncontrollable factors such as environmental factors or raw materials properties. The model's outputs are values one can measure or assess in terms of quality, productivity or cost. Many papers have been published to outline the advantages of these methods over the still prevalent trial and error approach. Even the epic and possibly futile struggle between those advocating traditional DOE and those advocating Taguchi methods has not challenged their value.

However, many companies do not apply these methods, even after making substantial efforts to train their staff. Various obstacles, especially in the case of production optimization, usually limit their applicability. Many difficulties arise when applying these methods to complex production problems.

- For some manufacturing processes, it may be difficult to carry out a factorial design because of high correlations between the factors. It may be impossible to cover a reasonable range of variation without generating bad or even unfeasible combinations for testing.
- Even if we assume that the experimental design is carried out with the full collaboration of operators and production managers (which is far from obvious, considering that a list of tests whose origin is sure to provoke incredulity), it might not be run as planned, especially if some production constraints exist. Too large discrepancies will make the analysis questionable.
- Changes cannot be made when conducting the experiment, even if the preliminary results demonstrate that the experimental plan is not appropriate.
- No error is allowed when running a test. A wrong combination will be discarded even if high costs were involved.

E.M. is a new method based on interactive experimentation to solve the above difficulties. The method includes three stages which are 1) building the feasible domain of the process 2) identifying the influential factors and fitting predicting equations and 3) optimizing the process window.

Building the feasible domain using interactive experimentation

Definition of the feasible domain

The feasible domain of the process is defined by the multidimensional volume in the continuous factor space, which best discriminates between accepted tests inside and rejected tests outside. A test is said accepted if the values or attributes of all the responses meet the selected specifications; it is said rejected if the value or attribute of at least one response is outside the specifications. This volume is fitted by a multidimensional ellipsoid which may be sculptured by the lower and upper limits of the factors. Figure 1 displays the feasible domain.

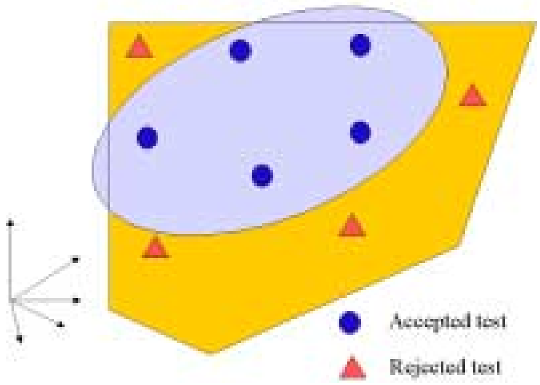

Figure 1. Feasible domain of the process as defined by the E.M. Method.

Building the feasible domain

The domain is built test after test and the selection of each next test is such as to maximize the gain in new information. For example, the new test which is identified by a question mark on Figure 2 is promising. If the test is accepted, the domain will be redefined to take into account this new direction of investigation. But if the test is rejected, the boundaries of the domain in this direction will now be known and causes of rejection will have been identified.

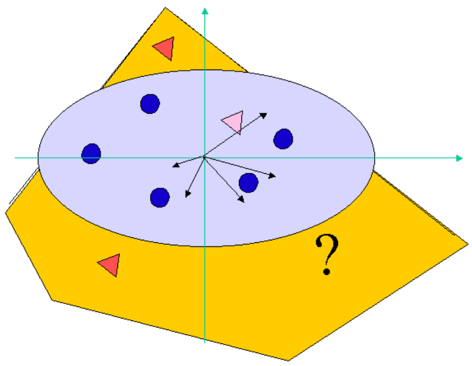

Figure 2. Choice of the next best test to run.

This interactive approach has many advantages :

- The selection of each new test is an opportunity for taking into account the current know-how about the process based on technical, scientific or intuitive expertise.
- The new information is saved by re-computing the feasible domain.
- Whether the test is accepted or rejected, it will improve our knowledge of the process.
- The formulation of the study may be questioned at any time, based on the sequential learning of the process behavior. It is then possible to add new factors or to change the specifications to account for new clues.
- Conducting precisely the selected test combination is not critical. Each test needs only to be run somewhere in the identified region and the actual values will be collected.
- Historical data can be used to start building the feasible domain. If not reliable, these data will be eliminated later, as soon as an approximate shape of the domain has been determined.
- The end of the experimentation process is based on expert judgment. If additional tests are necessary, the feasible domain will provide a visual support to assist in decision-making.
- All the data are important. It is useful to know that outside the feasible domain boundaries, a specific test has been rejected for a documented reason. In fact, the information associated with a rejected test is very important and has to be assessed with the distribution of the accepted tests.

Identifying influential factors and fitting predicting equations

Multiple regression analysis is used to search for an appropriate subset of predictors for deriving second-order polynomial regression models of the continuous responses. The collected data are not orthogonal and potential difficulties may arise due to multiple collinearities between predictors. Ridge analysis is helpful in selecting the key predictors which explain the variations of the responses and constructing a stable equation with a good predictive power.

Figure 3 shows isoresponse lines of a continuous response in a principal plane of the feasible domain.

Attributes of a discrete response will cluster along a logical scheme in the multidimensional space of the factors and provide a heuristic partition of the feasible domain as shown in Figure 3.

Discriminant analysis is used to identify the factors which best discriminate between the various categories of the response and to construct a stable model for predicting memberships.

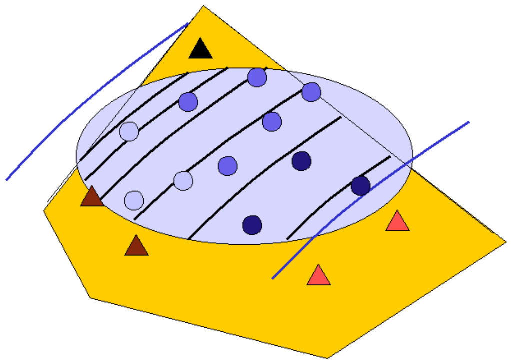

Figure 3. Isoresponses of a continuous response and attributes of a discrete response in a principal plane of the feasible domain.

Analyzing the results

Parameter design

Figure 4 shows two process modes and the isoresponses of a continuous response in a principal plane of the feasible domain. Mode A, which is located in a flat region of the response surface, is robust since the value of the response will not vary significantly, even if the factors are not under control.

On the contrary, Mode B, which is located in a steep region of the response surface, is not robust and even small variations of the factors will transmit high variation to the response.

Exploration of the feasible domain may provide satisfactory solutions and moving the process mode toward a more robust region does not involve new costs.

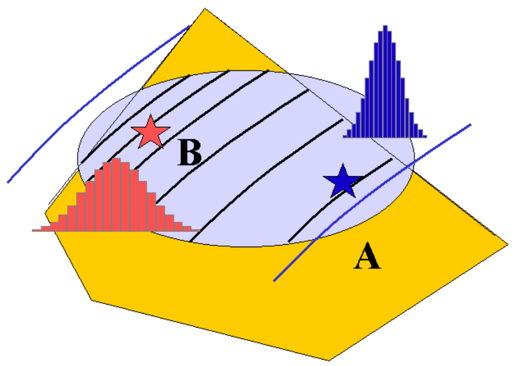

Figure 4. Parameter design for reducing variation.

There is no statistical method to extrapolate the solution to future production, for which the actual environment may be unknown. Expert knowledge of the feasible domain around the solution will provide the confidence which is needed to make this extrapolation.

Tolerance design

If the selected process mode does not provide the desired capability (six sigma capability for example), a tighter control will have to be exerted on some factors. Identifying the factor which contributes the most to the transmitted variation is important to avoid an expensive control embracing all the factors.

The Pareto diagram of Figure 5 indicates the contribution of each factor to the variation transmitted to the response. Here tighter control of factor 5 is required to increase the process capability.

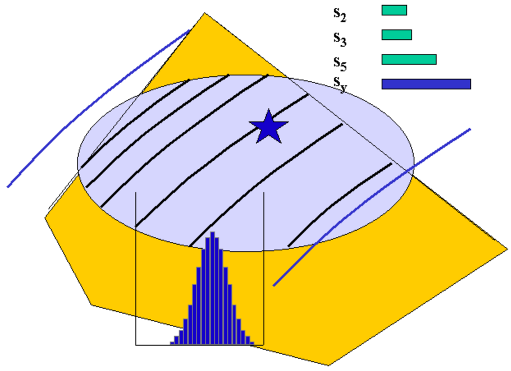

Figure 5. Contribution of the factors to the transmitted variation.

Visualizing the discrete responses

Displaying the attributes of the discrete responses on the principal planes of the feasible domain (see Figure 3) constitutes a powerful tool to understand the process behavior and to identify the areas where special problems may appear, for example the development of specific defects. The *E.M.* Method is applicable even if all the responses are discrete. The capacity to reproduce faults we want to avoid, will assist the decision maker in identifying a reliable solution.

Optimizing with conflicting criteria

Once our understanding of the results has been established, following an exploration of the feasible domain, one may search for an optimal solution based on various criteria which can be incompatible. The selection of 1) the multiple criteria (maximum, minimum or target values of a factor or a response), 2) their respective weights and 3) a tolerance margin to keep off the boundaries of the feasible domain is made only when a fair knowledge of the process has been achieved through interactive experimentation. The *E.M.* Method is a flexible tool to assist the decision maker in reassessing the selected criteria and adding new criteria to reduce costs.

Building the process window

The process window is constructed around the best possible process mode. Its size inside the multidimensional feasible domain is set by only one parameter and the units on each axis are defined by the assessed production tolerance of each factor. The window can be stretched as long as the process capability remains satisfactory. Figure 6 shows the process window around the point expressing the optimal solution. The process window may turn into a multidimensional scheme for monitoring the process evolution.

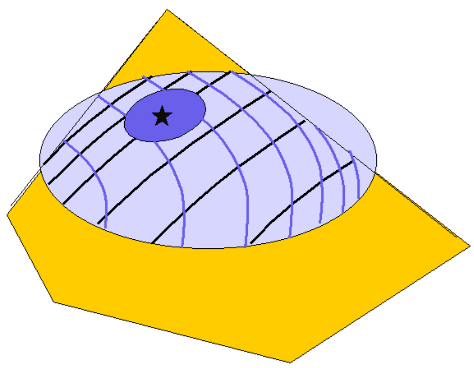

Figure 6. Process window around the point expressing the optimal solution.

Adaptation table

The optimisation of the process mode can be repeated for extreme values taken by some criteria. It is then possible to interpolate between these values to design an adaptation table which can be used for carrying out adaptive control.

A software to support the E.M. Method

The *E.M.* software puts into practice all the features of the *E.M.* Method.

- Visualization of the process behavior in the principal 2D planes of the feasible domain.
- Interactive display of the points representing the accepted and rejected tests, the isoresponses of continuous responses, the attributes of the discrete responses, the factors' axes, the variation ranges, …
- Computation of the best next test which maximizes the gain in new information.
- Simulation of the introduction of a new test to assess its leverage.
- Regression analysis taking into account possible multicollinearity problems.
- Estimation of the process capability and determination of the process window.
- Computation of the contribution of each factor to the variation transmitted to the responses.
- Multicriteria optimization in the feasible domain…

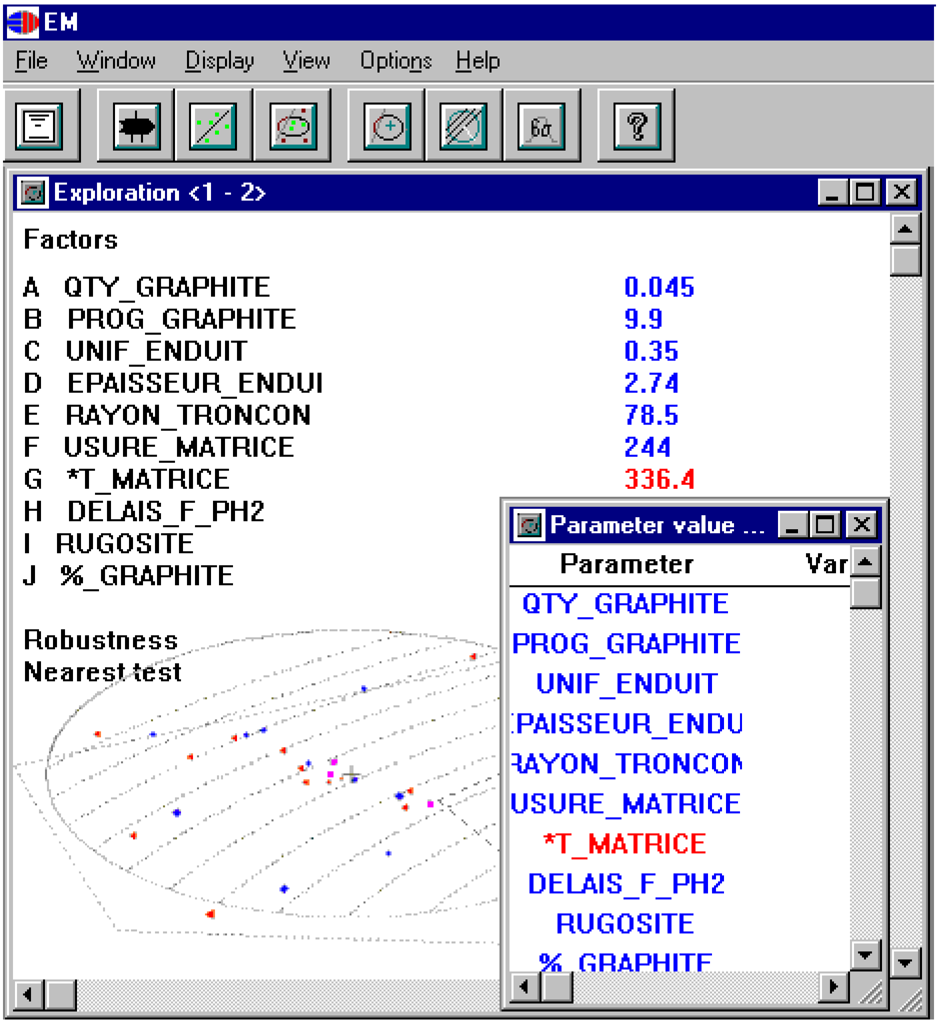

Figure 7. Typical view in the E.M. software.

Summary
The *E.M.* Method combines three functions for problem solving in the manufacturing industry:

- a Learning function to provide a good understanding of the process behavior, through interactive experimentation.
- a Reference function to monitor the process evolution within the process window which has been optimized inside the multidimensional feasible domain.
- a decision support function for decision making to get the best compromise between quality and productivity requirements, while minimizing costs.

The *E.M.* Method is a powerful tool for experimental design when the experiments are conducted in a production environment. *E.M.* is also applicable to product design and process development, and therefore is a suitable tool for concurrent engineering.