APPENDIX 1

INTRODUCTION TO STATISTICAL TECHNIQUES

Micro machining is one of the most important processes carried out in micro-manufacturing industry. Also micro-machining has become indispensable to the modern manufacturing industries. It is used directly or indirectly in the production of almost all the goods and services being created all over the world. In manufacturing environments, it is often a challenge to find an effective means of reducing costs and improving product quality. The continuous demand for higher productivity and product quality asks for better understanding and control of the machining process. A better understanding can be achieved through experimental measurement and theoretical simulations and modeling of the process and its resulting product. The experimentation plays an important role in Science, Engineering, and Industry. The experimentation is an application of treatments to experimental units, and then measurement of one or more responses. It is a part of scientific method. It requires observing and gathering information about how process and system work. In an experiment, some input x’s transform into an output that has one or more observable response variables y. Therefore, useful results and conclusions can be drawn by experiment. In order to obtain conclusion an experimenter needs to plan and design the experiment, and analyze the results.

It has long been recognized that conditions during micro-end milling, such as spindle speed, feed rate, and depth of cut, also for the micro-WEDG process such as feed rate, capacitance and voltage should be selected
to optimize the economics of micro-machining operations, as assessed by productivity, total manufacturing cost per component or some other suitable criterion. Taylor (1907) showed that an optimum or economic cutting speed exists which could maximize material removal rate. Manufacturing industries have long depended on the skill and experience of shop-floor machine-tool operators for optimal selection of cutting conditions and cutting tools. Considerable efforts are still in progress on the use of handbook based conservative cutting conditions and cutting tool selection at the process planning level. The most adverse effect of such a not-very scientific practice is decreased productivity due to sub-optimal use of machining capability. The need for selecting and implementing optimal machining conditions and the most suitable cutting tool has been felt over the last few decades. Despite Taylor’s early work on establishing optimum cutting speeds, progress has been slow since all the process parameters need to be optimized. Furthermore, for realistic solutions, the many constraints met in practice, such as low machine tool power, torque, force limits and component surface roughness must be overcome. The latest techniques for optimization include Taguchi method, Pareto ANOVA method, Taguchi quality loss function and Principal component analysis technique and response surface methodology.

TAGUCHI TECHNIQUE

The Taguchi technique involves reducing the variation in a process through robust design of experiments. The overall objective of the method is to produce high quality product at low cost to the manufacturer. The Taguchi method was developed by Dr. Genichi Taguchi of Japan who maintained that variation. Taguchi developed a method for designing experiments to investigate how different parameters affect the mean and variance of a process performance characteristic that defines how well the process is functioning. The experimental design proposed by Taguchi involves using orthogonal
arrays to organize the parameters affecting the process and the levels at which they should be varies. Instead of having to test all possible combinations like the factorial design, the Taguchi method tests pairs of combinations. This allows for the collection of the necessary data to determine which factors most affect product quality with a minimum amount of experimentation, thus saving time and resources. The Taguchi method is best used when there are an intermediate number of variables (3 to 50), few interactions between variables, and when only a few variables contribute significantly. The arrays are selected by the number of parameters (variables) and the number of levels (states). Analysis of variance on the collected data from the Taguchi design of experiments can be used to select new parameter values to optimize the performance characteristic. The data from the arrays can be analyzed by plotting the data and performing a visual analysis.

**Philosophy of the Taguchi technique**

1. Quality should be designed into a product, not inspected into it.

2. Quality is best achieved by minimizing the deviation from a target. The product should be designed so that it is immune to uncontrollable environmental factor. In other words, the signal (product quality) to noise (Uncontrollable factors) ratio should be high.

3. The cost of quality should be measured as a function of deviation from the standard and the losses should be measured system wide. This is the concept of loss function or the overall loss incurred upon the customer and society from a product of poor quality because the producer is also a member of society and because customer dissatisfaction will discourage future
patronage, this cause to customer and society will come to the producer.

Hence Taguchi’s parameter design is an important tool for robust design. It offers a single and systematic technique to optimize the design performance, quality and cost. Two major tools used in robust design are (Park 1996, Unal and Dean 1991, Phadke 1989)

a. Signal to noise ratio(S/N), which measures quality with emphasis on variation and

b. Orthogonal arrays, which accommodate many design factors simultaneously.

When a critical quality characteristics deviates from the target value it causes a loss. Continuously pursuing variable reduction from the target value in critical quality characteristics is the key to achieve high quality and reduce cost.

TAGUCHI DESIGN OF EXPERIMENTS

The general steps involved in the Taguchi technique are as follows:

1. Define the process objective, or more specifically, a target value for a performance measure of the process. The target of a process may also be a minimum or maximum. The deviation in the performance characteristic from the target value is used to define the loss function for the process.

2. Determine the design parameters affecting the process. Parameters are variables within the process that affect the performance measure can be easily controlled. The number of
levels that the parameters should be varied at must be specified. Increasing the number of levels, to vary a parameter at increases the number of experiments to be conducted.

3. Create orthogonal arrays for the parameter design indicating the number of and conditions for each experiment. The selection of orthogonal arrays is based on the number of parameters and the levels of variation for each parameter.

4. Conduct the experiments indicated in the completed array to collect data on the effect on the performance measure.

5. Complete data analysis to determine the effect of the different parameters on the performance measure.

In Taguchi method, S/N is used to represent a response or quality characteristic and the largest S/N ratio is required. There are usually three types of quality characteristics, i.e. target-the-best, larger-the-better and smaller-the-better.

1. Target-the-best: $S/N = 10 \log \frac{\bar{y}}{s_y}$ \hspace{1cm} (A1.1)

2. Larger-the-better: $S/N = -10 \log \frac{1}{n} \left( \sum \frac{1}{y^2} \right)$ \hspace{1cm} (A1.2)

3. Smaller-the-better: $S/N = -10 \log \frac{1}{n} \left( \sum y \right)$ \hspace{1cm} (A1.3)

where, $y$ is the measured data, $\bar{y}$ is the average of measured data, $s_y^2$ is the variance of $y$ and $n$ is the number of samples. For each type of the characteristics, with the above S/N ratio transformation, the higher the S/N ratio the better is the result.
TAGUCHI QUALITY LOSS FUNCTION (TQLF)

The following issues must be considered when applying the Taguchi method for the multiple quality characteristics optimization.

The attribute and loss functions in the multiple cases are always different for each quality characteristic. Therefore the loss for each quality characteristic cannot be compared and summed directly. The measurement units in the multiple cases are always different for each quality characteristic. Therefore the loss caused by each unit for each quality characteristic could be different. The importance in the multiple cases could be different for each quality characteristic. The adjustment factors should be chosen when the nominal the best quality characteristics exist in Multiple-response cases. This is especially true when one such factor is used to adjust the mean on target and a significant change occurs in the values of other quality characteristics.

The following steps can be used for solving the above issues.

1. Selection of machining parameters

   For any optimization problem selection of machining parameter is important one because of the success is mainly depends on the selected parameters and its range.

2. Selection of quality characteristics

   In Taguchi method there are three quality characteristics are considered, these are commonly used in industrial environment such as nominal-the-best, smaller-the-better and larger-the-better (Tong and Su 1997, Taguchi 1996, Phadke 1989, Taguchi et al 1993).

3. Determination of normalized quality loss for each response
The normalized quality loss ($C_{ij}$) can be calculated as follows

$$C_{ij} = \frac{(L_{ij}^- - L_{ij}^+)}{(L_i^+ - L_{ij}^-)}$$  \hspace{1cm} (A1.4)

where, $L_{ij} = \text{Quality loss for the } i^{th} \text{ quality loss for the } j^{th} \text{ experiment}$, $L_{ij}^+ = \text{Maximum quality loss for the } i^{th} \text{ quality characteristics}$ and $L_{ij}^- = \text{Minimum quality loss for the } i^{th} \text{ quality characteristics}$

4. Calculation of TNQL of each trail

$$TNQL = X_j = \sum w_i C_{ij}$$  \hspace{1cm} (A1.5)

where, $w_i = \text{the weight of } i^{th} \text{ normalized quality character}$ $(i = 1, 2, \ldots, m)$ and $m = \text{number of quality characteristics}$

5. Calculation of Multiple-response signal to noise ratio (MRSN)

$$MRSN = -10\log[X_j]$$  \hspace{1cm} (A1.6)

The optimal setting of each parameter is one which yields the maximum MRSN.

6. Testing of significant factor and interaction using ANOVA

7. Determination of optimized parameter levels

8. Conformation experiment for its validation

**PRINCIPAL COMPONENT ANALYSIS (PCA)**

PCA is a practical and systematic methodology for tackling Multiple-response problems in industrial experiments based on Taguchi’s PD methodology. The methodology utilizes TQLF and PCA. The author considers only static responses in Taguchi’s PD experiments: STB, LTB response and TTB response. The quality loss functions of these responses
(or quality characteristics) are well explained in many Taguchi textbooks (Taguchi 1996, Taguchi et al 1993). In the context of MSMs, PCA is generally performed for three purposes: data exploration, data reduction and data classification. The technique was first introduced by Pearson (1901) and a description of practical computing methods in PCA came much later from Hotelling. It is a data reduction technique used to identify a small set of variables that accounts for a large proportion of the variance in the original variables. For the present study, PCA is carried out to transform a set of responses or quality characteristics into a linear combination of uncorrelated components. Manly provides an excellent introduction to PCA and other MSMs such as factor analysis (FA), cluster analysis (CA), Discriminant Function Analysis (DFA) and so on. According to Manly, PCA does absolutely nothing when the responses are uncorrelated. The best results are obtained when the responses or quality characteristics are highly correlated, positively or negatively.

This methodology is developed for only static and continuous quality characteristics in industrial experiments. The methodology encompasses the following steps.

1. **Identify the control, signal and noise factors**

   For all PD experiments it is important that control, signal and noise factors which influence the response(s) of interest be identified by means of a thorough brainstorming session.

2. **Determine the type of response(s) or quality characteristics to be optimized**

   For PD experiments the following types of continuous measurable responses or quality characteristics are generally considered.
(a) Smaller-The-Better (STB) responses. A smaller-the-better response is one in which the desired goal is to obtain a measure of zero. Examples of this type of characteristic include tool wear, noise level in automotive engines, response time to customer complaints, shrinkage porosity, warp and surface roughness.

(b) Larger-The-Better (LTB) responses. This type of response is generally considered when the objective of the experiment is to maximize the response, but within the acceptable design limits. Examples of this type of characteristic include strength, efficiency, miles/gallon of an automobile, corrosion resistance, product or component reliability, product life, MRR and so on.

(c) Target-is-The-Best (TTB) responses. This characteristic is considered when the objective of the experiment is to achieve a desired target performance for the response. Examples of this type of characteristic include dimensions (width, thickness, height, etc.), force, pressure, viscosity, resistance, voltage, current, capacitance and so on. A target value is specified for this characteristic, and a minimal variability around the target is desirable. 3. Compute the Quality Loss (QL) per unit product for each response

The quality loss per unit product or item for each response or quality characteristic should be computed in this step. This can be easily obtained from TQLFs. Let $L_{ij}$ D quality loss for the $i^{\text{th}}$ response (or quality characteristic) at $j^{\text{th}}$ trial condition or experimental run, $L_i_\text{max}$ D maximum quality loss for $i^{\text{th}}$ response and $L_i_\text{min}$ D minimum quality loss for $i^{\text{th}}$ response.
4. Compute the normalized quality loss (NQL)

The normalized quality loss can be computed using Equation (A1.4)

5. Perform PCA on the NQL data

For Multiple-response problems, PCA can be considered to be an effective means of determining a small number of components (say k) which account for most of the variance in the original p responses, provided k ≤ p. Let X1, X2, ..., Xp be a set of responses; then, using PCA, we have the following uncorrelated linear combination of principal components:

\[ Z_1 = a_{11}X1 + a_{12}X2 + \ldots + a_{1p}X_p \]  \hspace{1cm} (A1.8)

subject to the condition that \( a_{11}^2 + a_{12}^2 + \ldots + a_{1p}^2 = 1 \). Here \( Z_1 \) is called the first principal component. The principal components are created in order of decreasing variance, so that the first principal component accounts for most variance in the data, the second principal component less, and so on. All the principal components are uncorrelated with each other. The variances of the principal components are called the Eigen values and it is important to note that the sum of the variances of the principal components is equal to the sum of the variances of the original responses. The coefficients of the principal components (i.e. \( a_{11}, a_{12}, \ldots \)) are called the eigenvectors. It is a matter of judgement as to how many components must be considered. The rule of thumb is to choose those components with an Eigen value greater than or equal to one. For Multiple-response problems in industrial experiments we can perform PCA on the NQL data derived from step 4. The larger the \( Z \) value (also called Multiple-response performance statistic), the better is the performance of the product.
6. Determine the optimal condition

The optimal condition is the one which yields the maximum Z value. The Z value (i.e. Multiple-response performance statistic) at each factor level must be computed and then we identify the factor/interaction effects which significantly influence the Multiple-response performance statistic. Here the Multiple-response performance statistic can be treated as an individual response on which statistical analysis will be performed.

7. Perform a confirmatory experiment

A confirmatory experiment is performed to verify the final optimal factor settings and to see whether or not the optimal condition derived by the experiment actually yields an improvement in product quality. If the results from the confirmatory experiment are conclusive, a specific action on the product or process must be taken for improvement. On the other hand, if unsatisfactory results are obtained, further investigation of the problem may be required.

**RESPONSE SURFACE METHODOLOGY**

Response surface methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving and optimizing process (Douglass c. Montgomery 2002). It is a technique for determining and representing the cause and effect relationship between the responses and input control variables influencing the responses as a two or three dimensional hyper surface. The accuracy and the effectiveness of an experimental design depends on careful planning and execution. The steps involved in this research work for the experimental investigation include the following:

I. Identifying the important process control variables.
II. Finding the upper and lower limits of the control variables, viz., feed rate, capacitance and voltage.

III. Development of design matrix using central composite design and conducting the experiments as per the design matrix.

IV. Recording the responses of MRR and surface roughness.

V. Development of second order quadratic model.

VI. Determining the coefficients of the second order polynomials.

VII. Checking the adequacy of the models developed.

VIII. Testing the significance of the regression coefficients.

IX. Presenting the main effects and the significant interaction effects of the process parameters on the responses in two (contour) and three dimensional (surface) graphical form.

X. Determination of optimized machining process parameters for the multiple responses.

CENTRAL COMPOSITE DESIGN (CCD)

CCD is the most popular second order design which was introduced by Box and Wilson (1951). It is a factorial or fractional factorial design with centre points and star points. The star points are added to estimate the curvature. The factorial design points in CCD contribute to the estimation of the interaction terms. The axial points contribute in a large way to the estimation of quadratic terms. Without the axial points, only the sum of the quadratic terms can be estimated. The factorial points do not contribute to the estimation of quadratic terms. The centre runs provide an internal estimate of error (pure error) and contribute toward the estimation of quadratic terms. The areas of flexibility in the use of central composite design reside in the
selection of axial distance ($\alpha$) and the number of centre runs ($n_c$). The choice of these parameters is very important. The choice of $\alpha$ depends to a greater extent on the region of operability and region of interest. The choice of $n_c$ often has an influence on the distribution of variance in the region of interest. The axial distance value $\alpha$ is chosen to maintain rotatability and it depends on the number of experimental runs in the factorial portion of the central composite design. In this work, 32 experimental design points were considered including 5 centre points.

MULTIPLE RESPONSE OPTIMIZATIONS

In most of the modern technological situations, more than one response variable is pertinent to the success of an industrial process or system. In this research work, the influence of feed rate, capacitance and voltage on the MRR and surface roughness (multiple responses) is investigated. Further the optimal machining parameters are determined by simultaneously maximizing the MRR and minimizing the surface roughness. A desirability function based simultaneous optimization technique popularized by Derringer and Suich (1980) is used in this work. In this approach, each response $Y_i$ is first converted into an individual desirability function $d_i$ that varies between 0 and 1 ($0 \leq d_i \leq 1$). Here $d(Y_i)=0$ represents a completely undesirable value of $Y_i$ whereas $d(Y_i)=1$ represents a completely desirable or ideal response value. The individual desirabilities are then combined using the geometric mean, which gives the overall desirability $D$ as below:

$$D = \sqrt[m]{d_1 \times d_2 \times \ldots \times d_m} = (d_1 \times d_2 \times \ldots \times d_m)^{\frac{1}{m}} \quad \text{(A1.9)}$$

where, $m$ is the number of responses. From the Equation (A1.1) it is clear that, if any response $Y_i$ is completely undesirable ($d(Y_i)=0$), then the overall
desirability is zero. The geometric mean of overall desirability in this case is as follows:

\[ D = (d_{MRR} \times d_{Ra})^{\frac{1}{2}} \]  
(A1.10)

Depending on whether a particular response \( Y_i \) is to be minimized, maximized or assigned a target value, different desirability functions \( d(Y_i) \) can be used. In this case, MRR is to be maximized while \( R_a \) and TWR is to be minimized. If the objective for the response is a minimum value

\[
d(Y_i) = \begin{cases} 
1 & \text{if } Y_i < T \\
(U - Y_i))^r & \text{if } T \leq Y_i \leq U \\
0 & \text{if } Y_i > U 
\end{cases}
\]  
(A1.11)

If the objective for the response is a maximum value, then the desirability function is

\[
d(Y_i) = \begin{cases} 
0 & \text{if } Y_i < L \\
(Y_i - L)^r & \text{if } L \leq Y_i \leq T \\
1 & \text{if } Y_i > T 
\end{cases}
\]  
(A1.12)

where \( L \) and \( U \) are the lower and upper limit values respectively, \( T \) is the target values and \( r \) is the weight. When the weight value is 1, the desirability function is linear. Choosing the weight value greater than one \((r>1)\), places more emphasis on being close to the target value and choosing the weight in between 0 and 1\((0< r<1)\) makes this less important. Equations (A1.3) and (A1.4) are used to minimize TWR and \( R_a \) and maximize MRR respectively. The value of weight is taken as 1\(( r=1 )\) to make the desirability function linear.
APPENDIX 2

SPECIFICATION OF MICRO-MACHINE TOOL USED

CUSTOM BUILT MINIATURIZED MICRO END MILLING MACHINE

The experimental works were carried out in a three axis custom-built miniaturized micro-end milling machine. Two stages of sizes 120x120mm (Surega Seiki-KS 103-70) and 120x160mm (KS 103-100) were built for X-Y and Z (spindle axis) axes respectively. The maximum travel of X-Y stage is 70mm whereas the maximum travel of Z stage is 100mm. The spindle is driven by the compressed air and the spindle speed varies from 60,000 to 80,000 rpm. Aluminium block of 60x40x16mm is used as the work-piece material and carbide end-mill cutter of diameter 1mm as the cutting tool.

MIKROTOOLS DT-110
High Precision Multi-Process Machine-Tool
Description

High Precision Multi Process Machine Tool should be capable of performing multiple machining processes such as Micro Turning, Micro Milling, Micro EDM, Micro ECM, Micro EDG and Micro Wire EDM. The machine provides high precision motion transmission with negligible backlash, low deformation and negligible vibration in order to achieve high accuracy in machined components.
<table>
<thead>
<tr>
<th><strong>Mikrotools DT-110 Specification</strong></th>
<th><strong>Description and/or Specification</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>overview General Features</strong></td>
<td></td>
</tr>
<tr>
<td>Machine base/ configuration</td>
<td>Monolithic natural granite table is used as the machine base. Y axis module is mounted on the granite base. X axis and Z axis are mounted on gantry type cast iron structure which is also mounted on the granite base.</td>
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<tr>
<td>Vibration isolation</td>
<td>4-point heavy duty passive dampers</td>
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<tr>
<td>Machine travels</td>
<td>Maximum travel:</td>
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<tr>
<td></td>
<td>X – 200mm, Y – 100mm, Z – 100mm</td>
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<tr>
<td>Position accuracy</td>
<td>+/- 1 micron/100mm</td>
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<tr>
<td></td>
<td>+/- 0.3 micron over any 25mm of travel</td>
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<tr>
<td></td>
<td>+/- 5 micron over the entire machine travel</td>
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<tr>
<td>Position feedback system</td>
<td>Optical linear scale with resolution of 0.1 m (100 nm)</td>
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<td></td>
<td>RS422 (TTL) compromise</td>
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<tr>
<td>Control system</td>
<td>Mikrotools original motion controller with original GUI</td>
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<td></td>
<td>Standard NC code compatible</td>
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<td></td>
<td>Extended NC codes for EDM related control</td>
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<tr>
<td>Linear axis guide</td>
<td>Linear guide way system for all linear axes with high precision grade</td>
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<tr>
<td>Linear drive systems</td>
<td>Digital AC servo motor with full-closed feedback control. High precision grade ball screw driving mechanism with preload</td>
</tr>
<tr>
<td>Specification</td>
<td>Value</td>
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<tr>
<td>-------------------------------</td>
<td>----------------------------------------------------------------------</td>
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<tr>
<td>Slide straightness</td>
<td>+/- 3 micron/100mm</td>
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<td></td>
<td>+/- 0.3 micron over any 25mm of travel</td>
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<tr>
<td>Slide feed rate</td>
<td>Conventional machining: Min: 1 mm/min, Max: 2000 mm/min</td>
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<td></td>
<td>EDM/ECM: Min: 0.2 micron/sec, Max: 800 micron/sec</td>
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<tr>
<td>Slide stiffness</td>
<td>350 N/m</td>
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<tr>
<td>Spindle type</td>
<td>Digital AC servo motor driven precision angular contact ball bearing structure. Electrically isolated from the machine body which enables the EDM and ECM process</td>
</tr>
<tr>
<td></td>
<td>Motor Power: 100W</td>
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<tr>
<td>Spindle speed range</td>
<td>Rating: 0~3000 rpm, max.: 5000 rpm</td>
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<tr>
<td>Spindle axial stiffness</td>
<td>120 N/m</td>
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<tr>
<td>Tool clamping</td>
<td>Precision grade collect system (ER-11)</td>
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<tr>
<td></td>
<td>Spindle run-out: Max. 2 micron</td>
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<tr>
<td>Hybrid Power Supply</td>
<td>Fully integrated power supply for micro EDM and ECM process application</td>
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<tr>
<td></td>
<td>Micro EDM application</td>
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<tr>
<td></td>
<td>- Voltage: 80~150V</td>
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<td></td>
<td>- Discharge circuit: RC relaxation</td>
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<td></td>
<td>- R: 1 K fixed</td>
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<td></td>
<td>- C: 0, 10 pF, 100 pF, 1nF, 10nF, 100nF, 400nF</td>
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<tr>
<td></td>
<td>Micro ECM application</td>
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<td>- Voltage: 0.5 ~ 30V</td>
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<td></td>
<td>- Max current: 3A</td>
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<td>- Pulse e on-time: 1~999 micro seconds</td>
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<td>- Pulse off-time: 1~999 micro seconds</td>
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Coolant system

Two type of coolant supply system for EDM and ECM with completely separated reservoir, filter, pump and work tank

Enclosure

Automatic door system for operation safety

Utility requirements

Compressed air:

6 bar for door open/close for flushing unit option (under development)

Electrical: 220V AC 50/60 Hz

Single phase Max Current 20 A

Floor Space: 3 meters width, 2 meters depth, 2.5 meters height.