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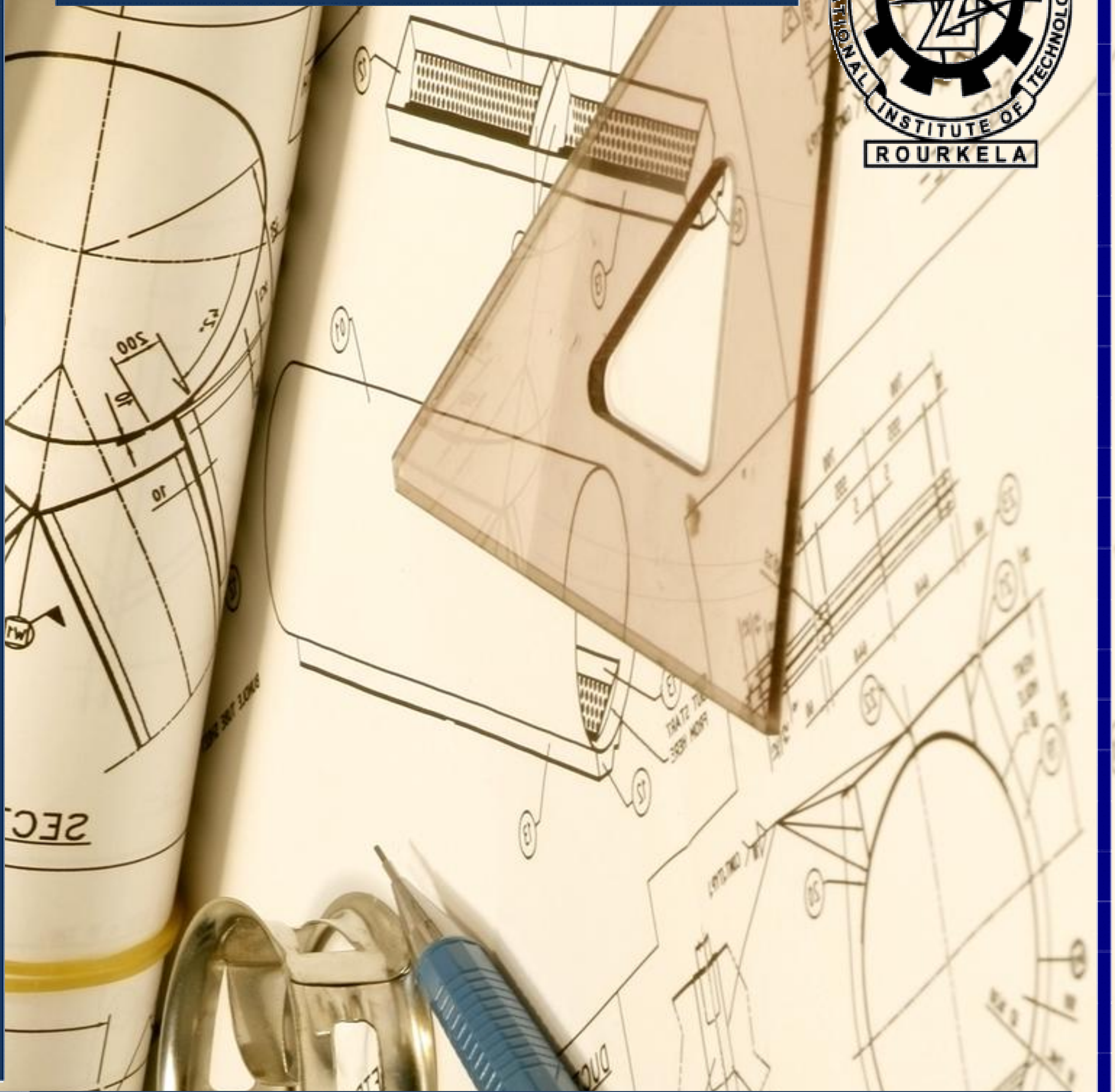
Advanced Manufacturing



TEACHING LEARNING BASED OPTIMIZATION APPLIED TO MECHANICAL CONSTRAINED DESIGN PROBLEMS

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Teaching Learning based Optimization Applied to Mechanical Constrained Design Problems

by

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CERTIFICATE

This is to certify that M. Tech thesis entitled, "Teaching Learning based Optimization Applied to Mechanical Constrained Design Problems" submitted by V Rakesh Kumar in partial fulfillment for the requirements of the award of Master of Technology degree in Mechanical Engineering at National Institute of Technology - Rourkela is an authentic work carried out by him under my supervision and guidance. He has fulfilled all the prescribed requirements and the thesis, which is based on candidate's own work, has not been submitted elsewhere.

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Dedicated to my loving father

Rajendra Sharma

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Abstract

Amidst all the evolutionary optimization algorithms Teaching–Learning-Based Optimization (TLBO) seems to be a promising technique with relatively competitive performances. It outperforms some of the well-known metaheuristics regarding constrained benchmark functions, constrained mechanical design, and continuous non-linear numerical optimization problems. This dissertation presents the application of TLBO to various problems of mechanical engineering. Both constrained and unconstrained optimization has been performed on some manufacturing processes and design problems. Parametric optimization of three non-conventional machining processes namely electro-discharge machining, electro-chemical machining and electro-chemical discharge machining, have been carried out and the results are compared with other evolutionary algorithms. Improvement in the existing TLBO algorithm has been incorporated in this dissertation using two schemes namely bit string mutation and replacement of worst solutions with fresh ones. Performance evaluation of these modifications have been presented in this dissertation by solving six optimization problems using original TLBO and proposed modifications. It has been found that better results are achieved in reaching the global optimal values by the use of these modifications. However, the results prefer the use of bit string mutation over scheme of replacing the worst solutions with fresh solutions in addition to the original logic of TLBO. The bit wise mutation and replacement of the worst solutions with fresh ones, proved an added advantage to the existing algorithm. Both these modifications resulted in a steeper convergence rate and finally provided global optimal solutions, and in some cases even better solutions than previously published results. With the use of better optimization techniques, it is now possible for the process engineers to reach near optimal parametric setting of various machining process in a real time manufacturing environment.

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Chapter 1: Introduction

1.1 Non Conventional Machining Processes

Conventional machining processes require that the work piece material to be stressed beyond the yield point to achieve material removal. This certainly requires the cutting tool to be harder than the work piece material. Alloys with alloying elements such as tungsten, chromium, vanadium, molybdenum etc, have high hardness, high heat resistance and high strength to weight ratio. Machining of such alloys by conventional means is difficult as well as time consuming. Hence, there is a need to develop better machining processes to handle the shortcoming of the conventional processes. As a result, these processes are termed as non-traditional machining methods.

The main reasons for the development and use of new machining processes are stated below.

1. *High strength alloys or brittle materials:* The hardness of the work piece material (typically above 400HB) is often harder than the cutting tool material or when it becomes necessary to machine hardened materials.
2. *Complex shapes and surfaces:* Particularly in manufacturing of moulds and dies, complex shapes and surfaces are required to be produced on already hardened materials. In such cases, it is a necessity to use more advanced machining processes. Sometimes, the work piece is too flexible, slender, or delicate to withstand the cutting or grinding forces, or the parts are too difficult to fix.
3. *Accuracy and surface finish:* High accuracies on dimensions and better surface finish on hard materials are often produced by slow conventional machining accompanied by a number of finishing processes. This makes the process uneconomical and time consuming. Also the temperature rise and residual stresses in the work piece are not desirable or acceptable.
4. *Difficult geometry:* With addition to complex geometries, it is also required to produce long holes with length to diameter ratio greater than 100 or produce holes of diameter less than 0.1 mm.

These requirements have led to the development of chemical, electro-chemical, thermal, electro-thermal, mechanical, and other means of material removal. Over the last four decades, there has been a large increase in the number of non-traditional machining processes (NTMP) [1]. Today, non-traditional machining processes with vastly different capabilities and specifications are available for a wide range of applications. These processes are classified according to the nature of energy employed in machining as discussed below [1]:

1 Chemical and electro-chemical processes like chemical milling, electro-chemical machining, electro-chemical grinding, electro-chemical honing etc.
2 Thermal and electro-thermal processes like electric discharge machining, laser beam machining, plasma arc machining, electron beam machining, and ion beam machining etc.
3 Mechanical processes like ultrasonic machining, abrasive jet machining, and water jet machining etc.
4 Hybrid processes like electro-chemical discharge grinding, abrasive electrical discharge machining, vibration-assisted electro-chemical machining etc.

1.1.1 Electro-Discharge Machining (EDM)

Formation of craters by electric discharges on cathode was first reported by Joseph Priestley in 1766. His observations are as follows [2]:

“After discharging a battery, of about forty square feet, with a smooth brass knob, I accidently observed upon it a pretty large circular spot, the centre of which seemed to be superficially melted. (…) After an interruption of melted places, there was an entire and exact circle of shining dots, consisting of places superficially melted, like those at the centre.”

“Examining the spots with a microscope, both the shining dots that formed the central spot, and those which formed the external circle, appeared evidently to consist of cavities, resembling those in the moon, as they appear through a telescope, the edges projecting shadows onto them, when they were held in the sun.”

Since then electric discharges have been used for a variety of tasks including material removal which was attempted by Russian scientists Boris and Natalya Lazarenkoat at Moscow University in 1943. The interest in spark machining initiated a number of studies and research in the 1950s.

The schematic diagram of an EDM process is shown in Figure 1.The work piece is attached to the X-Y Table which is electrically attached to the positive terminal of the power supply. The tool is electrically attached to the negative terminal of the power supply and is either made of brass, copper, graphite or stainless steel. It is attached to the tool holder and feeding mechanism which are servo controlled. The dielectric pump constantly delivers dielectric between the inter electrode gap (IEG). A DC pulse generator is used to supply the power for the machining operation. The mechanism of material removal in a discharge process can be summarised as follows [2]:

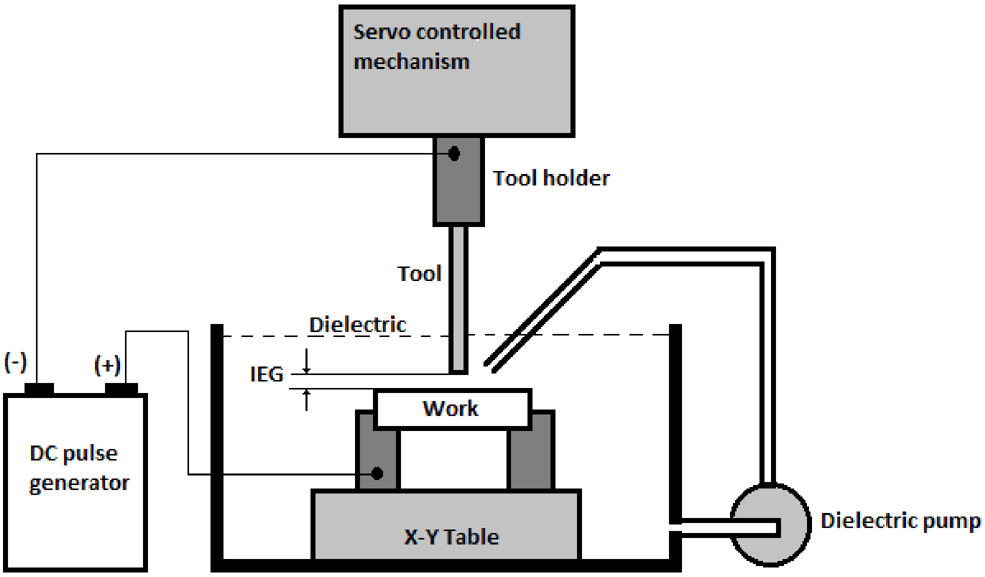

Figure 1. Schematic diagram of EDM process

1. With the application of voltage, an electric field builds up between the two electrodes at the position of least resistance. The ionization leads to the breakdown of the dielectric which results in the drop of the voltage and the beginning of flow of current.
2. Electrons and ions migrate to anode and cathode respectively at very high current density. A column of vapor begins to form and the localized melting of work commences. The discharge channel continues to expand along with a substantial increase of temperature and pressure.
3. When the power is switched off the current drops; no further heat is generated, and the discharge column collapses. A portion of molten metal evaporates explosively and/or is ejected away from the electrode surface. With the sudden drop in temperature the remaining molten and vaporized metal solidifies. A tiny crater is thus generated at the surface.
4. The residual debris is flushed away along with products of decomposition of dielectric fluid. The application of voltage initiates the next pulse and the cycle of events."

Also, due to the inertia of the surrounding fluid, the pressure within the spark becomes quite large and may possibly assist in 'blasting' the molten material from the surface leaving a fairly flat and shallow crater. The amount of metal removed per spark depends upon the electrical energy expended per spark and the period over which it is expended [2].

1.1.2 *Electro-Chemical Machining (ECM)*

The basis of the ECM process is the phenomenon of electrolysis - the laws established by Faraday in 1833. The principle and equipment used in the ECM process are illustrated in Figure 2. The work piece and tool are the anode and cathode respectively of an electrolytic cell and a constant potential difference (usually about 5-30 V) is applied across them producing a high current density of 10–200 A/cm

A suitable electrolyte (NaCl or NaNO3 aqueous solution) is chosen so that the cathode shape remains unchanged during electrolysis. The electrolyte is pumped at a rate of 3-60 m/s, through the gap between the electrodes to remove the machining waste (i.e. dissolved material, usually metal hydroxide) and to diminish unwanted effects such as those that arise with cathodic gas generation and electrical heating. The rate at which metal is then removed from the anode is approximately in inverse proportion to the distance between the electrodes. As machining proceeds and with the simultaneous movement of the cathode at a typical rate, e.g. 0.02 mm/s towards the anode, the gap width along the electrode length will gradually tend to reach a steady state value. Under these conditions, a shape that is approximately a negative mirror image of the cathode will be reproduced on the anode as the cathode does not alter during the ECM process. A typical gap width then can be about 0.4 mm.

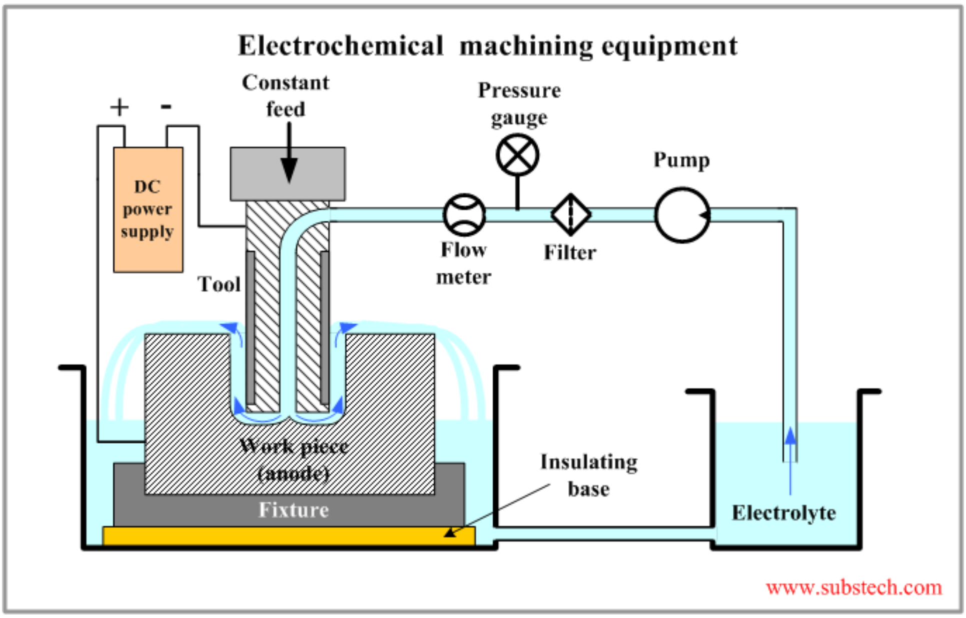

Figure 2 : Schematic diagram of ECM process

The ECM process can handle a large variety of materials limited only by their electro-chemical properties and not by their strength. This process is characterized by high metal removal rates for high-strength and difficult-to-machine alloys. Fragile parts that are not easily machinable can be shaped by the ECM process. Certain characteristics of the ECM process such as the ability to machine three-dimensional curved surfaces without the striation marks, stress-free and burr-free machining, no thermal damage to the work piece, and ideally no tool wear etc., make this process widely applicable. However, the main limitation of the ECM process is the high initial investment along with high power consumption and large floor space requirement. Therefore, use of this process is a costly affair. This problem is further compounded by the corrosion, toxicity, and safety-related problems of the electro-chemical machining process. Also, electro-chemical machining is a complex process and it is difficult to predict the changes that may occur in the inter-electrode gap. The electrolyte properties vary due to the emission of a considerable amount of heat and gas bubbles. In addition, hydrodynamic parameters such as pressure also vary along the electrolyte flow direction and make the analysis quite complicated.

1.1.3 Electro-Chemical Discharge Machining

Electro-chemical discharge machining (ECDM) is a non-traditional machining process which combines the attributes of both Electro-chemical machining (ECM) and Electro-discharge machining (EDM) [3]. Similar to the ECM process when a voltage is applied across the tool and auxiliary electrode, reduction of electrolyte with liberation of hydrogen gas takes place at the cathode tip. When the applied voltage is increased beyond a threshold value, hydrogen gas bubbles evolve in large number at the tip of cathode and grow in size. Their nucleation site density increases, current path gets restricted between cathode and electrolyte interface causing discharge to occur at this interface instantly. Thus, discharge in ECDM always occurs when the voltage in an electrolytic cell is increased beyond a threshold value [4]. Figure3 shows the schematic diagram of the ECDM. The tool is attached to the tool holding and feeding arrangement while the auxiliary electrode is place just beneath the work piece holding platform. The level of electrolyte in machining chamber is constantly maintained such that the inter-electrode gap (IEG) is sufficiently flooded with electrolyte at all times.

ECDM is a very recent technique in the field of advanced machining to machine electrically non conductive materials using electro-chemical discharge phenomenon [5]. This process can be used to machine hard and high strength to weight ratio materials. Also, intricate designs can be machined. One of the major advantages of ECDM over ECM or

EDM is that the combined metal removal mechanisms in ECDM yields a much higher machining rate [3].

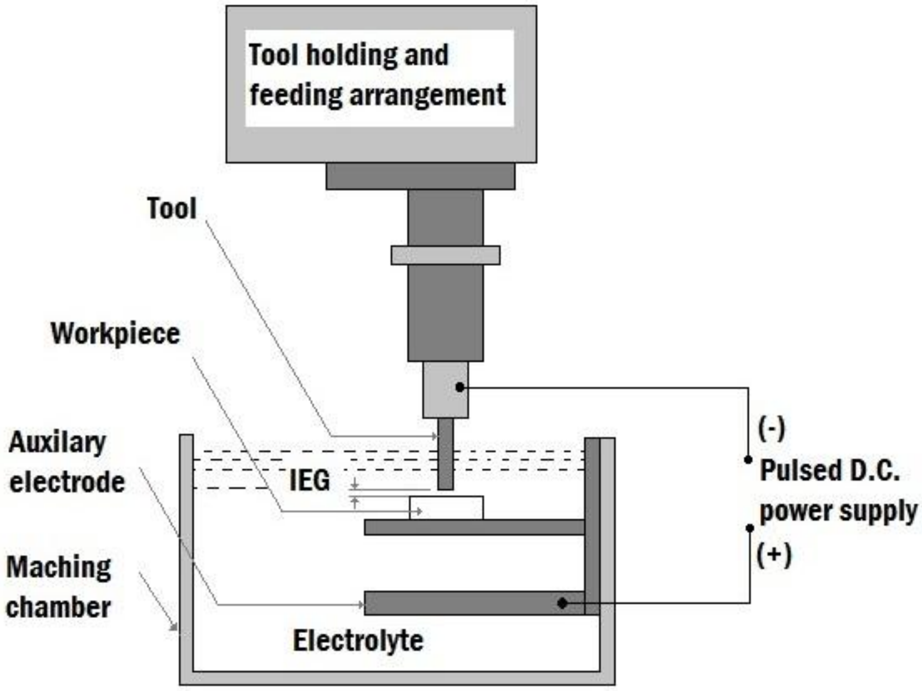

Figure 3 : Schematic diagram of ECDM process

Non-traditional machining has always been a costly affair due to high initial investment cost, high power consumption, safety requirements and large floor area. This problem is further aggravated by the corrosion, toxicity, safety-related problems, high power electrical grids, automation requirements and many more. Non-conventional machining have always been a complex process involving precise mechanisms which makes the total machining process unpredictable and sensitive to the controlling parameters. The hydrodynamic parameters of the electrolyte or dielectric such as pressure, flow, temperature etc. also influence the machining performance. Hence, it is imperative to know the correct optimal settings of the controlling parameters for a cost effective machining. In this thesis, three non-conventional machining processes (already described) are considered for the parametric optimization of controlling parameters.

1.2 Design of Mechanical elements

Engineering design of mechanical elements is described by very large numbers of variables and it is imperative for the designer to specify appropriate values for these variables. Skilled designers often use their expert knowledge, experience, and judgment to specify these variables to design effective engineering elements. Because of the complexity and large size of a typical design task, even the most expert designers are unable to consider all the variables at the same time. Design optimization of mechanical elements is defined as the application of optimization algorithms and techniques to the problems in engineering design in order to help the designers in improving the system's performance, weight, reliability, and/or cost. In this thesis, three elements from the mechanical domain have been considered. The design problem associated with all the three elements considered [6] are solved using evolutionary algorithms and a few results have also been compared with those of conventional techniques and other evolutionary algorithms.

1.2.1 Pressure Vessel Design

Cylindrical or spherical pressure vessels (e.g. hydraulic cylinders, gun barrels, pipes, boilers and tanks) are commonly used in industry to carry both liquids and gases under pressure. When the pressure vessel is exposed to this pressure, the material comprising the vessel is subjected to pressure loading and hence stresses from all directions. The normal stresses resulting from this pressure are functions of the radius of the element under consideration, the shape of the pressure vessel (i.e. open ended cylinder, closed end cylinder, or sphere) and the applied pressure. Two types of analysis are commonly applied to pressure vessels. The most common method is based on a simple mechanics approach and is applicable to "thin wall" pressure vessels which by definition have a ratio of inner radius ® to wall thickness (t) of $r/t \geq 10$. The second method is based on elasticity solution and is always applicable regardless of the r/t ratio and can be referred to as the solution for "thick wall" pressure vessels. Both types of analysis are discussed here, although for most engineering applications, the thin wall pressure vessel can be used.

For analysis of thin-walled pressure vessels, several assumptions are made which are as follows.

1. Plane sections remain plane
2. The ratio $r/t \geq 10$ with t being uniform and constant
3. The applied pressure (p) is the gage pressure (note that p is the difference between the absolute pressure and the atmospheric pressure)
4. Material is linear-elastic, isotropic and homogeneous.
5. Stress distributions throughout the wall thickness do not vary
6. Element of interest is remote from the end of the cylinder and other geometric discontinuities.
7. Working fluid has negligible weight

Cylindrical Vessels: A cylindrical pressure with wall thickness, t, and inner radius, r, is considered (see Figure 4). A gauge pressure, p, exists within the vessel by the working fluid (gas or liquid). For an element sufficiently removed from the ends of the cylinder and oriented as shown in Figure 12.1, two types of normal stresses are generated: hoop, σ_h , and axial, σ_a, that both exhibit tension of the material and are represented by σ1andσ2respectively.

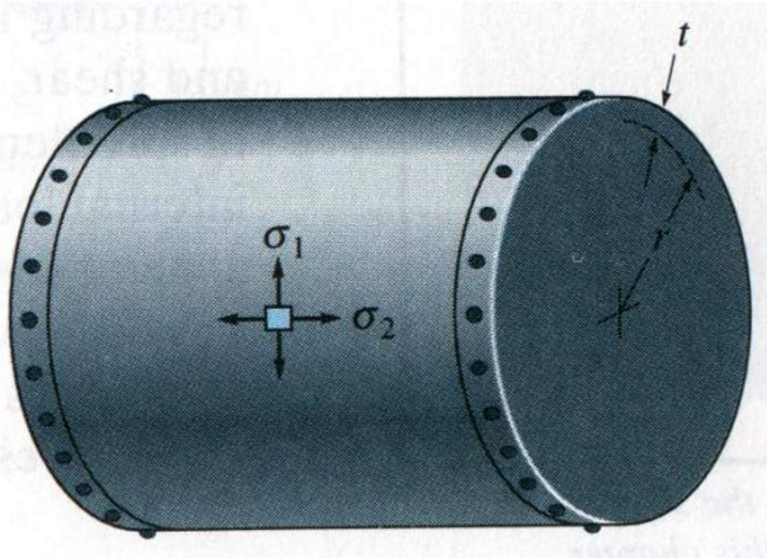

Figure 4 : Cylindrical Thin-Walled Pressure Vessel

For the hoop stress, consider the pressure vessel section by planes sectioned by planes a, b and c for Figure 5. A free body diagram of a half segment along with the pressurized working fluid is shown in Figure 6. Note that only the loading in the x-direction is shown and that the internal reactions in the material are due to hoop stress acting on incremental areas, A, produced by the pressure acting on projected area, Ap. For equilibrium in the x-direction we sum forces on the incremental segment of width dy to be equal to zero such that:

$$\sum F_x = 0$$

$$2[\sigma_h A] - pA_p = 0 = 2[\sigma_h\, t\, dy] - p\, 2r\, dy$$

$$\text{or solving for } \sigma_h \qquad (1)$$

$$\sigma_h = \frac{pr}{t}$$

Where dy = incremental length, t = wall thickness, r = inner radius, p = gauge pressure, and σ_h is the hoop stress.

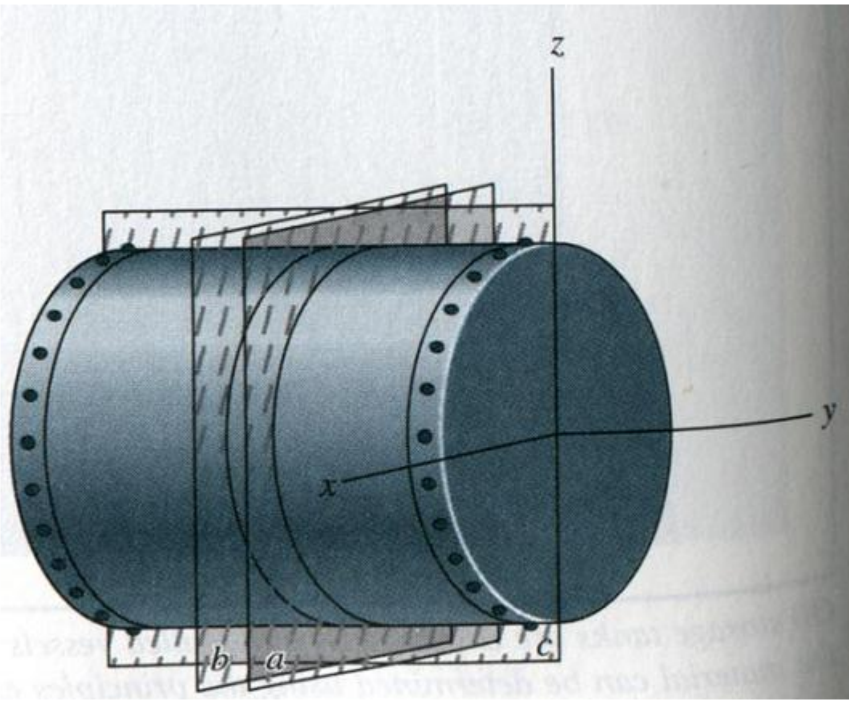

Figure 5. Cylindrical Thin-Walled Pressure Vessel Showing Coordinate Axes and Cutting Planes

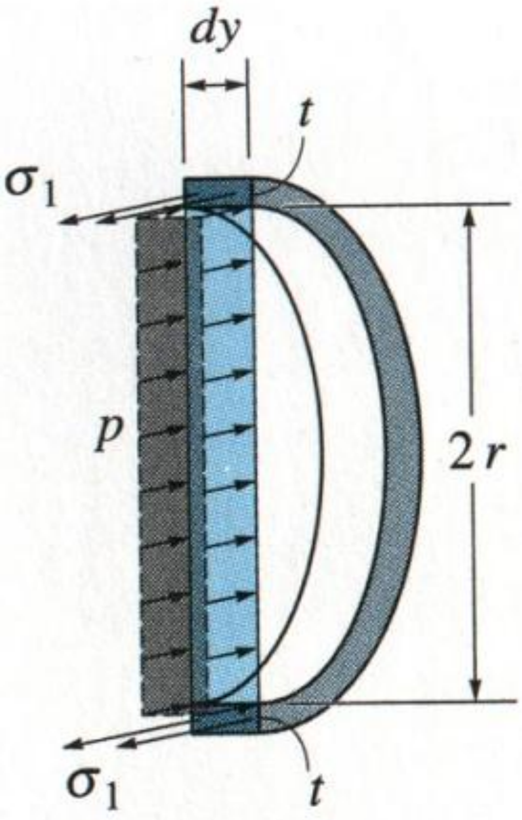

Figure 6 : Free-Body Diagram of Segment of Cylindrical Thin-Walled Pressure Vessel

For the axial stress, consider the left portion of section b of the cylindrical pressure vessel shown in Figure 7. A free body diagram of a half segment along with the pressurized working fluid is shown in Figure 7. Note that the axial stress acts uniformly throughout the wall and the pressure acts on the end cap of the cylinder. For equilibrium in the y-direction we sum forces such that:

$$\sum F_y = 0$$

$$\sigma_a A - pA_e = 0 = \sigma_a \pi (r_o^2 - r^2) - p\pi r^2$$

$$or\ solving\ for\ \sigma_a$$

$$\sigma_a = \frac{p\pi r^2}{\pi (r_o^2 - r^2)}$$

$$substituting\ r_o = r + t\ gives$$

$$\sigma_a = \frac{p\pi r^2}{\pi([r+t]^w - r^2} = \frac{p\pi r^2}{\pi(r^2 + 2rt + t^2 - r^2)} = \frac{p\pi r}{(2rt + t^2)} \quad (2)$$

since this is a thin wall with a small t

t is smaller and can be neglected such that after simplification.

$$\sigma_a = \frac{pr}{2t}$$

$$where\ r_o is\ the\ inner\ radius\ and\ \sigma_a\ is\ the\ axial\ stress$$

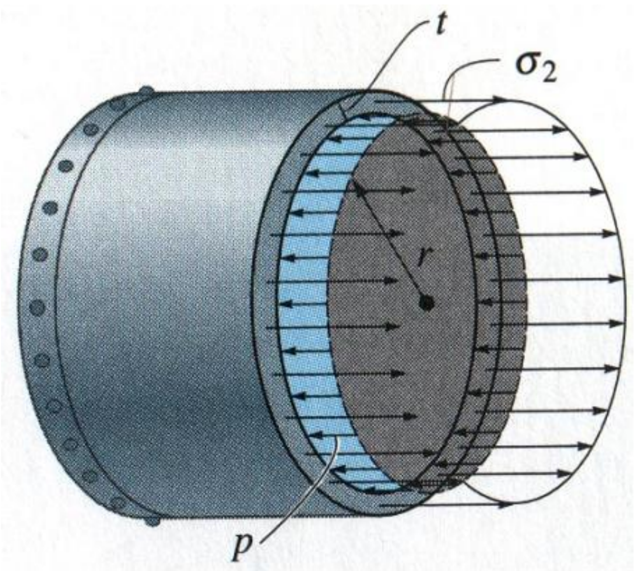

Figure 7 : Free-Body Diagram of End Section of Cylindrical Thin-Walled Pressure

Note that in Equations 1 and 2, the hoop stress is twice as large as the axial stress. Consequently, when fabricating cylindrical pressure vessels from rolled-formed plates, the longitudinal joints must be designed to carry twice as much stress as the circumferential joints.

1.2.2 Welded Beam design

The optimization problem of a welded beam is a simplified example of many complex

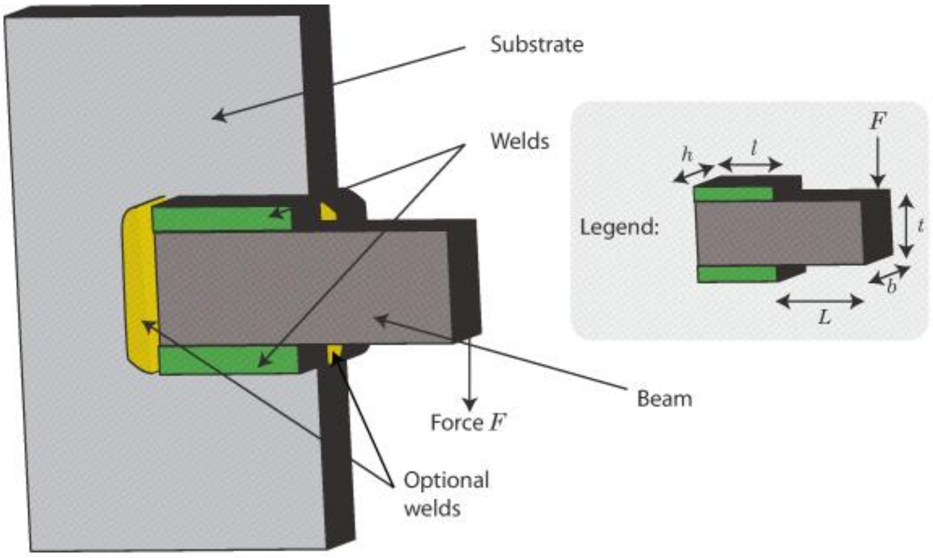

Figure 8 : Nomenclature in welded beam

design issues arising in structural engineering, which deals with designing the steel beams and connecting them to form large and complex structures like bridges, buildings, etc. It is used by many researchers as a benchmark problem for optimization. The problem of designing an optimal welded beam consists of dimensioning a welded steel beam and the welding length so as to minimize its cost subjected to constraints on shear stress, bending stress in the beam, the buckling load on the bar, the end the deflection of the beam, and side constraints. There are four design variables: which are shown with the letters (h, l, t, and b) in the Figure 8. Structural analysis of this beam leads formulation of objective functions subject to seven nonlinear constraints. The objective function can be evaluated by considering the different cost associated with the fabrication of the welded beam. This cost may or may not include material cost, labor cost, additional cost etc. These decisions are under the discretion of the designer during the formulation of the optimization problem.

The different generic constraints can be those related to shear stress, bending stress, buckling load, end deflection or geometric feasibility. Formulations of few of them have been discussed below. It is to be noted that the allowable values for different parameters are decided after well consideration of the factor of safety.

Shear stress constraint- The shear stress in the weld must be less than the maximum shear stress of the weld material. Generally the weld metal is similar to the base metal. Let

$\tau(x)$ be the shear stress in the material and τ_{max} be the maximum shear stress allowed. Thus the mathematical formulation can be given by Equation 3.

$$\tau(x) \leq \tau_{\max} \tag{3}$$

Bending stress constraint- The maximum bending stress induced in the beam should be less than the maximum allowed bending stress. Again this could be mathematically expressed as in Equation 4.

$$\sigma(x) \leq \sigma_{\max} \tag{4}$$

Here $\sigma(x)$ represents the bending moment induced in the beam and σ_{max} is the allowable maximum bending stress.

Geometrical constraints-The geometric feasibility plays an important role in the physical application of any design. It is quite obvious that in this problem the thickness of the weld bead (h) cannot be greater than the breadth of the beam (b). This can be mathematically expressed as in Equation 5.

$$h \leq b \tag{5}$$

End deflection constraint- For the design to successfully serve its intended purpose many physical deformations and displacements are limited. One such limitation may also be imposed on the design of welded beam. The end deflection should not be greater than the fixed numerical value. This constraint can be mathematically formulated as in Equation 6.

$$\delta(x) \leq \delta_{\max} \tag{6}$$

Where $\delta(x)$ is the end deflection in the welded beam, while δ_{max} is the maximum end deflection decided by the designer.

Many such constrains can be formulated and applied to the optimization problem of the design of welded beam. One such problem is detailed in Chapter 4 of this thesis.

1.2.3 Tension-Compression Spring Design

A spring is an elastic object used to store mechanical energy. Springs are usually made out of spring steel. Small springs can be wound from pre-hardened stock, while larger ones are made from annealed steel and hardened after fabrication. Some non-ferrous metals are also used including phosphor bronze and titanium for parts requiring corrosion resistance and beryllium copper for springs carrying electrical current (because of its low electrical resistance).

When a spring is compressed or stretched, the force it exerts is proportional to its change in length. The rate or spring constant of a spring is the change in the force it exerts, divided by the change in deflection of the spring. That is, it is the gradient of the force versus deflection curve. An extension or compression spring has units of force divided by distance, for example lbf/in or N/m. Torsion springs have units of force multiplied by distance divided by angle, such as N·m/rad or ft·lbf/degree. The inverse of spring rate is compliance, that is: if a spring has a rate of 10 N/mm, it has a compliance of 0.1 mm/N. The stiffness (or rate) of springs in parallel is additive, as is the compliance of springs in series.

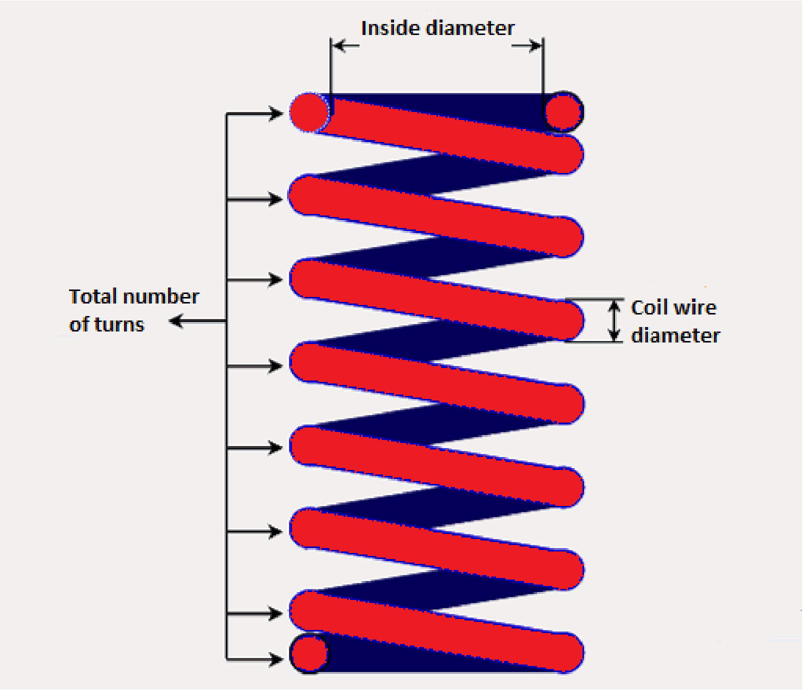

Figure 9 : Nomenclature of a tension-compression spring

Depending on the design and required operating environment, any material can be used to construct a spring, so long as the material has the required combination of rigidity and elasticity: technically, a wooden bow is a form of spring. Figure 9 shows the nomenclature of a generic spring considered for the design optimization.

The designing of tension springs is same as that of compression springs except for the end hook that is found in tension springs only. The coils in a tension spring are usually wound tightly together so that there exists an initial tension F_i of magnitude approximating 15-25% of maximum external load. This force is used to hold the spring accurately and do not deflect until the external force is greater than the inbuilt tension.

Thus the deflection is given by the Equation 7

$$y = \frac{8(F - F_i)D^3 i}{Gd^4} \quad (7)$$

And the spring stiffness is given by the Equation 8

$$k = \frac{F - F_i}{y} \quad (8)$$

So the total load is the summation of initial load and load required for desired extension, which is given by the Equation 9

$$F = F_i + ky \quad (9)$$

The stress produced in the wire of the spring at any cross section is due to the torsion and direct shear. So the basic design follows Equation 10

$$\tau = K \frac{8FD}{\pi d^3} \quad (10)$$

The stress produced in the spring is due to bending moment F_{rm} and direct force F and is given by the Equation 11

$$\sigma = K_1 \frac{32Fr_m}{\pi d^3} + \frac{4F}{\pi d^2} \quad (11)$$

Where: $K1$ is the stress concentration factor, r_m and r_i is the mean radius and inside radius of hook respectively

1.3 Evolutionary Methods for Optimization

Analytical or numerical methods have been applied to engineering computations since a long time to calculate the extreme values of a function. These methods may perform well in many practical cases but they fail in more complex design situations [6]. In real manufacturing problems, the number of machining parameters can be very large and their influence on the value to be optimized (the objective function) can be very complicated having nonlinear character. The objective function may be multimodal (i.e. have many local minimum or maximum), whereas the researcher is always interested in the global optimal values within the search space. Such problems cannot be handled by classical methods (e.g. gradient methods) at all as they converge at local optimal values [6]. In such complex cases, advanced optimization algorithms offer solutions to the problems because they find a solution near to the global optimum within reasonable time and computational effort. These techniques are stochastic in nature with probabilistic transition rules. These techniques are comparatively new and gaining popularity due to certain properties which the deterministic algorithm does not have. The examples include Genetic Algorithm (GA) [7], Differential Evolution (DE) [8]- [9], Particle Swarm Optimization (PSO) [10]- [11], Simulated annealing

(SA) [12], Artificial Bee Colony (ABC) [13] [14] [15] [16] etc. A few of them which are used in this thesis are discussed below.

1.3.1 Genetic algorithm (GA)

GA is an evolutionary algorithm technique which borrows the idea of survival of the fittest amongst an interbreeding population to create a search strategy [7]. It uses only the fitness value and no other knowledge is required for its operation. It is a robust search technique different to traditional algorithms which tend to be more deterministic in nature and get stuck up at local optima. The three basic operators of GA are reproduction, crossover and mutation. Initially, a finite population of feasible solutions to a specified problem is maintained. Through reproduction, it then iteratively creates new populations from the old by ranking the solutions according to their fitness values. Crossover leads to interbreeding the fittest solutions to create new off-springs which are optimistically closer to the optimum solution to the problem at hand. As each generation of solutions is produced, the weaker ones fade away without producing off-springs, while the stronger mate, combining the attributes of both parents, to produce new and perhaps unique off-springs to continue the cycle. Occasionally, mutation is introduced into one of the solution strings to further diversify the population in search for a better solution.

1.3.2 Simulated annealing (SA)

Simulated annealing is so named because of its analogy to the process of physical annealing of solids in which a crystalline solid is heated and then allowed to cool very slowly until it achieves its most regular possible crystal lattice configuration (i.e. its minimum lattice energy state) and thus is free of crystal defects. If the cooling schedule is sufficiently slow, the final configuration results in a solid with such superior structural integrity. Simulated annealing establishes the connection between this type of thermo- dynamic behaviour and the search for global minima for a discrete optimization problem. Furthermore, it provides an algorithmic means for exploiting such a connection [12]. At each iteration of a simulated annealing algorithm, the objective function generates values for two solutions (the current solution and a newly selected solution) which are then compared. Improved solutions are always accepted while a fraction of non-improving (inferior) solutions are accepted in the hope of escaping local optima in search of global optima. The probability of accepting non-improving solutions depends on a temperature parameter which is typically non-increasing with each iteration of the algorithm. The key algorithmic feature of simulated annealing is that it provides a means to escape local optima by allowing hill-climbing moves (i.e. moves which worsen the objective function value) which occur less frequently as the temperature parameter is finally decreased to zero.

1.3.3 Artificial Bee Colony (ABC)

Inspired by the intelligent foraging behaviour of honey bee swarms, the ABC algorithm was introduced to handle unconstrained benchmark optimization functions) [13] [14] [15] [16], similar to other well-known meta-heuristic algorithms. The colony of artificial bees consists of three groups: employed, onlookers, and scout bees. The employed bees randomly search for food-source positions (solutions). Then, by dancing, they share information (communicate) about that food source such as nectar amounts (solutions qualities) with the onlooker bees waiting in the dance area at the hive. The duration of a dance is proportional to the nectar's content (fitness value) of the food source being exploited by the employed bee. Onlooker bees watch various dances before choosing a food-source position according to the probability proportional to the quality of that food source. Consequently, a good food-source position attracts more bees than a bad one. Onlookers and scout bees, once they discover a new food-source position, may change their status to become employed bees. When the food-source position has been visited (tested) fully, the employed bee associated with it abandons it and may once more become a scout or onlooker bee. In a robust search process, exploration and exploitation processes must be carried out simultaneously [14]. In the ABC algorithm, onlookers and employed bees perform the exploration process in the search space while, on the other hand, scouts control the exploration process.

All the nature-inspired algorithms such as GA, SA and ABC require algorithm-specific parameters to be set for their proper working in addition to the common control parameters of population size and number of generations. The major advantage with the proposed Teaching Learning based Optimization (TLBO) Algorithm is that it only requires the control over a few common parameters as compared to other evolutionary techniques. This makes the proposed algorithm almost parameter less [17] [6] [18].

1.3.4 Teacher-Learning Based Optimization (TLBO)

TLBO is the simulation of a classical school learning process proposed by Rao et al. [17] [18] that consists of two stages. During the first stage, called Teacher Phase, a teacher imparts knowledge directly to his/her students. The better the teacher, the more knowledge the students obtain. However, the possibility of a teacher's teaching being successful during the Teacher Phase, in practice, is distributed under Gaussian law. There are only very rare students who can understand all the materials presented by the teacher (i.e., the right end of the Gaussian distribution). Most students will partially accept new learning materials (i.e., the mid part of the Gaussian distribution) and, in some cases, the teacher will have almost no direct effect on students' knowledge (i.e., the left end of the Gaussian distribution). However, the possibility for most students to obtain new knowledge is not completely lost. During the second stage, called Learner Phase, a student may learn with the help of fellow students. Overall, how much knowledge is transferred to a student does not only depend on his/her teacher but also on interactions amongst students through peer learning.

Teacher phase

It is first part of the algorithm where learners learn through the teacher. During this phase a teacher tries to increase the mean result of the class room from any value M_1 to his or her level. But practically it is not possible and a teacher can move the mean of the class room M_1 to any other value M_2 which is better than M_1 depending on his or her capability. Considered M_j be the mean and T_i be the teacher at any iteration i. Now T_i will try to improve existing mean M_j towards it so the new mean will be T_i designated as M_{new} and the difference between the existing mean and new mean is given by Equation 12.

$$Difference\_Mean_i = r_i(M_{new} - T_F M_j) \qquad (12)$$

Where T_F is a teaching factor that decides the value of mean to be changed and r_i is a random number in the range [0, 1]. The value of T_F can be either 1 or 2, which is again a heuristic step and decided randomly with equal probability as given in Equation 13.

$$T_F = round\ [1 + rand(0,1)\{2-1\}] \qquad (13)$$

The teaching factor is generated randomly during the algorithm in the range of 1-2, in which 1 corresponds to no increase in the knowledge level and 2 corresponds to complete transfer of knowledge. The in between values indicates amount of transfer level of knowledge. The transfer level of knowledge can be any depending on the learners' capabilities. In the present work, attempt was carried out by considering the values in between 1-2, but any improvement in the results was not observed. Hence to simplify the algorithm the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria. However, one can take any value of T_F in between 1-2.Based on this *Difference_Mean*, the existing solution is updated according to Equation 14.

$$X_{new,i} = X_{old,i} + Difference\_Mean_i \qquad (14)$$

Learner phase:

It is second part of the algorithm where learners increase their knowledge by interaction among themselves. A learner interacts randomly with other learners for enhancing his or her knowledge. A learner learns new things if the other learner has more knowledge than him or her. Mathematically the learning phenomenon of this phase is expressed in Equation 15.

At any iteration i, considering two different learners X_i and X_j where $i \neq j$

$$\begin{aligned} X_{new,i} &= X_{old,i} + r_i (X_i - X_j) \quad If \ f(X_i) < f(X_j) \\ X_{new,i} &= X_{old,i} + r_i (X_j - X_i) \quad If \ f(X_j) < f(X_i) \end{aligned} \qquad (15)$$

Accept X_{new} if it gives better function value.

Chapter 2: Literature Review

2.1 Electro-Discharge Machining (EDM)

A thermal model simulating discharge super position and capable of representing post-EDM surfaces was presented by Izquierdo [19]. It was concluded that location, discharge and development of temperature fields on irregular surfaces affected the material removal rate as much as 50% due to the superposition of multiple discharges. Using a finite element based model and considering the effect of superposition of multiple discharges the temperature fields inside the work piece was calculated and based on this the machined surface was generated.

Tantra et al. [20] proposed a combination of Taguchi and TOPSIS method in solving the multi-response parameter optimization problem in green-EDM. Multi-criteria decision making was performed on the developed analytical and the ranking of responses was based on the scores obtained by the summation of final global preference weights. A Triangular variation was used to give preference values to the output responses in the fuzzy domain. Based on the closeness coefficient values, combinations were identified for the factor levels for the optimal machining performance. This analysis of closeness coefficients identified that the peak current was the most influencing parameter in multi-performance characteristics.

An anode erosion model was developed by Patel [21]. This model assumed a Gaussian-distributed heat flux on the surface of anode material. It was also assumed that the area upon which the heat flux was incident increased with time. A simple cathode erosion model using the photoelectric effect as the dominant source of energy was augmented with energy balance for gas discharge and presented by Dibitonto[22]. Coguz [23] investigated on the machined surface profile of 2080 tool steel under variation of machining parameters. It was found that the increase in discharge current, pulse duration and dielectric flushing pressure increase the surface. The obtained surface profile information was transferred to computer in digitized form and was then modeled in the form of Fourier series.

A model on cylindrical plasma and variable mass was presented by Eubank [24]. Three differential equations considering energy balance, radiation and fluid dynamics were combined with plasma equations of state. Electron balance procedure was adopted to handle problems with the zero-time boundary conditions. Electro-discharge texturing based on the effect of dielectric fluid and change in the resistance in the dielectric during each voltage pulse was modeled by McGeough and Rasmussen [25]. The theoretical predictions were consistent with the practical findings that the length of the voltage _on time and peak current determined the surface roughness in texturing.

Thangadurai and Asha [26] attempted to evaluate the performance of electric discharge machining during machining of AA6061-wt.10% B4Cp metal matrix composite. Response surface methodology combined with Box-Behnken design (BBD) of experiments was used for the modeling of EDM process responses like material removal rate, tool wear rate and surface roughness. The input parameters considered for the modeling were current, pulse on-time and pulse off-time. The analysis of variance suggested the use of non-linear quadratic models to model the experimental data points of BBD. All factors were found to be significant in the determination of surface roughness while only current and pulse on-time were dominant on material removal rate. An error of 5% was calculated during a consistency check between the theoretical and experimental findings.

2.2 Electro-Chemical Machining (ECM)

A two-dimensional inter-electrode gap model was proposed by Bhattacharyya et al. [27].The numerical model of the metal removal rate was considered as an objective function with the electrolyte flow velocity and tool feed rate as the design variables. The three constraints considered were passivity, temperature and choking. The authors considered only a single-objective optimization problem and optimized it using a less accurate graphical solution technique. This model was based on many simple assumptions, such as the constant void fraction and electrolyte conductivity as a function of the void fraction only, constant electrolyte pressure throughout its flow path.

A cost model of the ECM process was proposed by El-Dardery [28]considering various costs involved in the machining process. The cost equation comprised of decision variables, namely electrolyte flow rate, feed rate and voltage. The combination of optimum values of decision variables were obtained by partial differentiation of the cost function with respect to decision variables. The values of decision variables obtained were not practical as no constraints were considered for the model. Hewidy et al. [29]analyzed the different components of ECM cost (such as costs of machining, cost of electrolyte used , cost of power consumption and cost of labor) with the objective to meet the practical production requirements of a company by setting the basic principles for selecting an electro-chemical machine. The authors stated the impossibility of having a generic model for this purpose. In other work, Hewidy et al. [30]modeled the performance of low-frequency vibrations assisted ECM by using an analytical approach.

Acharya et al. [31]presented a multi-objective optimization model for the ECM process with minimization of dimensional inaccuracy, maximization of the material removal rate and maximization of tool life as conflicting objectives. The decision variables considered were tool feed rate, electrolyte flow velocity, and applied voltage. The constraints considered were those of passivity, temperature and choking. Linearizing the objective functions and constraint equations by regression analysis was done to solve the optimization problem by goal programming. This model surpassed the limitations of the model proposed by Bhattacharyya et al. [27]but did not considered the variable bounds for feed rate and differences in the inter-electrode gap. The shortcomings of the model proposed by Acharya et al. [31] were overcome by Choobineh and Jain [32]. As tool life is overachieved in most practical cases, only two objective functions were considered, i.e. maximization of the material removal rate and maximization of dimensional accuracy and the third objective to maximize the tool life was eliminated. The authors used vertex method to find appropriate distribution of the objective functions. The modified goal-programming problem was then solved in the same way as in Acharya et al. [31].

Jain and Jain [33] presented the optimization model based on the analysis given in Acharya et al. [31] with modifications such as expanding the range of variable bound for the tool feed rate and electrolyte flow velocity without linearizing the objective functions and constraints. Single objective optimization to minimize the dimensional inaccuracy was done by employing genetic algorithm. However the passivity constraint was violated in their approach. Rao et al. [1] attempted to verify any further improvement in the solution by using some other optimization techniques such as particle swarm optimization (PSO) to the same optimization model. PSO was employed in this work for single-objective and multi-objective optimization of electro-chemical machining process parameters. The optimization model given in Acharya et al. [31] was considered by expanding the variable bound ranges for the tool feed rate and electrolyte flow velocity.

2.3 Electro-Chemical Discharge Machining (ECDM)

The ECDM phenomenon is explained by various researchers based on their experimental studies. Crichton and McGough [34] performed streak photography to get insight into the various stages of discharge by applying an 85 V pulse for a duration of 200 μs. They concluded that electrical discharge between cathode tool and electrolyte interface occurs due to: (a) generation of electrolytic gas at the surface of electrodes; (b) the growth of layers of low ionic concentration near the electrodes and formation of oxide films on the anode surface; and (c) the local variations in the electrolyte flow pattern caused by flow stagnation and eddy. These researchers have identified the reasons for discharge but the cause of discharge or the origin of driving force which is needed for discharge to take place has not been dealt with. Basak and Ghosh [35] had developed theoretical model for material removal rate and then estimated the nature of MRR characteristics under different input conditions. The experimental result indicates that, the MRR can be substantially increased by introducing an additional inductance in the circuit. Various control parameters involved in the ECDM process are electrolyte, temperature, applied voltage, inductance, current, pulse density, discharge frequency, etc. Kulkarni et al. [4] proposed the basic mechanism of temperature rise and material removal through experimental observations of time-varying current in the circuit. Wuthricha and Fasciob[36] had reviewed the machining of non-conducting materials like glass or ceramics using electro-chemical discharge machining with more focus on experimental difficulties. Mediliyegedara et al. [3] presented the new developments in process control for the hybrid ECDM process and carried out a system identification experiment to obtain the dynamics of the system and a process control algorithm was implemented.

Sarkar et al. [37]described the development of a second order, non-linear mathematical model for establishing the relationship among machining parameters during an ECDM operation. Various parameters considered were applied voltage, electrolyte concentration and inter-electrode gap and the responses includes material removal rate, radial overcut and thickness of heat affected zone. The model was developed based on response surface methodology and finally the output of the work recommended that applied voltage has significant effects on all the responses as compared to other machining parameters.

Samanta and Chakraborty [13]used the advanced optimization technique for the parameter optimization for ECDM process. Artificial bee colony algorithm was used to maximize material removal rate and minimization of heat affected zone and operating cost. Rao and Kalyankar [17] presented a comparative study between Steepest Ascent, Artificial Bee Colony and Teaching learning based Optimization algorithms in terms of population size, number of generations and computational time.

2.4 Constrained mechanical design problems

Sandgren [38]proposed an algorithm for the solution of nonlinear mathematical programming problems containing integer, discrete, zero-one, and continuous design variable. The algorithm implemented a branch and bound procedure in conjunction with either a quadratic programming method or exterior penalty function. Variable bounds were independently handled from design constraints which removed the necessity of reformulation of the problem at each branching node. Examples were also presented demonstrating the utility of the algorithm for solving design problems.

Kannan and Kramer [39] also proposed an algorithm for the solution of nonlinear mathematical programming problems containing integer, discrete, zero-one, and continuous design variable. The augmented Lagrange multiplier method combined with Powell's method and Fletcher and Reeves Conjugate Gradient method were used to solve the optimization problem wherein penalties were imposed on the constraints for integer/discrete violations. Several case studies were presented to illustrate the use of this algorithm. Coello [40] presented the proposal of using co-evolution to adapt the penalty factors of a fitness function incorporated in a genetic algorithm for numerical optimization. The solutions produced were better than those previously reported in the literature for other techniques that have been fine-tuned using a lengthy trial and error process to optimize a certain problem or set of problems. The technique presented was also easy to implement and was suitable for parallelization.

Ray and Liew[41] introduced an optimizing algorithm based on the fact social interactions enable individuals to adapt and improve quickly than biological evolution based on genetic inheritance alone. The algorithm exploited the intra and intersociety interactions within a formal society and the civilization model to solve single objective constrained optimization problems. Montes and Coello [42] presented a multi-member evolution strategy (SMES) to solve global nonlinear optimization problems. The approach did not require the use of a penalty function nor any extra parameters (besides those used with an evolution strategy). Instead, it used a diversity mechanism by allowing infeasible solutions to remain in the population. This technique helped the algorithm to reach the near global. The approach was tested with published benchmarks. The results stated that the computational cost (measured by the number of fitness function evaluations) is lower than the required cost of the other techniques compared.

Parsopoulos and Vrahatis [43] investigated the performance of the recently proposed Unified Particle Swarm Optimization method on constrained engineering optimization problems. A penalty function approach was employed and the algorithm was modified to preserve feasibility of the encountered solutions. The algorithm was applied on four well–known engineering problems with better results. He and Wang [44] employed the notion of co-evolution to adapt penalty factors and proposed a co-evolutionary particle swarm optimization approach (CPSO) for constrained optimization problems. The proposed CPSO was population based and easy to implement in parallel where, penalty factors also evolved using PSO in a self-tuning way. Results for well-known constrained engineering design problems demonstrated the effectiveness, efficiency and robustness on initial populations of the proposed method. Moreover, the CPSO obtained some solutions better than those previously reported by various researchers.

Huang et al. [45] presented a differential evolution approach based on a co-evolution mechanism, named CDE to solve constrained problems. A special penalty function was designed to handle the constraints and then a co-evolution model was presented and differential evolution (DE) was employed to perform evolutionary search in spaces of solutions and penalty factors. The solutions and penalty factors evolved interactively and self-adaptively, and satisfactory solutions and suitable penalty factors were obtained simultaneously. Simulation results based on many benchmark functions demonstrated the effectiveness, efficiency and robustness of the proposed method.

Liu et al. [46] proposed a hybrid algorithm named PSO-DE, which integrated particle swarm optimization (PSO) with differential evolution (DE) to solve constrained numerical and engineering optimization problems DE was incorporated to update the previous best positions of particles forcing PSO to jump out of stagnation. The hybrid algorithm increased the convergence and improved the algorithm's performance. Testing was done on 11 well-known benchmark test functions and five engineering optimization functions. Comparisons revealed that PSO-DE outperformed or performed equally to seven state-of-the-art approaches in terms of quality of the resulting solutions.

Akay and Karaboga[47] used the Artificial Bee Colony (ABC) algorithm to solve large scale optimization problems, and engineering design problems by extending the basic ABC algorithm by adding a constraint handling technique in the selection step of ABC algorithm in order to give preference to the feasible regions of entire search space. Nine large scale unconstrained test problems and five constrained engineering problems were solved by using the ABC algorithm and the performance was compared against those of state-of-the-art algorithms.

Ragsdell and Phillips [48] illustrated the sensitivity of a design to variations in uncontrollable parameters. The procedure was applied to the design of welded beam structures which resulted in low-cost design with minimal sensitivities. Dominant constraints were chosen which contained variations of uncontrollable parameters. A dual objective function was formed and trade-off curves were presented from which the optimal solution was selected. The minimization was carried out using generalized reduced gradient.

Leandro and Viviana [49] presented combinations of an ant colony inspired algorithm (ACA) and chaotic sequences (ACH) and employed it in well-studied continuous optimization problems of engineering design. Two case studies were described and evaluated. The results indicated that ACA and ACH handled such problems efficiently both in terms of precision and convergence, and in most applications they outperform previous published results.

Chapter 3: Parametric Optimization of Non-Conventional Machining

Non traditional machining has always been a costly affair due to high initial investment cost, high power consumption, safety requirements and large floor area. This problem is further aggravated by the corrosion, toxicity, safety-related problems, high power electrical grids, automation requirements and many more. Non conventional machining have always been a complex process involving precise mechanisms which makes the total machining process unpredictable and sensitive to the controlling parameters. The hydrodynamic parameters of the electrolyte or dielectric such as pressure, flow, temperature etc. also influence the machining performance. Hence it is imperative to know the correct optimal settings of the controlling parameters for a cost effective machining.

The operators or the planners generally go by the provided manual or by their own experience to select the parametric values. Such decisions fall short of efficiency and effectiveness of the overall machining performance. To assist the operators and researchers to select the optimal parametric values this thesis presents three non conventional processes with intent to find the optimal process parameters. Keeping in view the complex non-linear mathematical formulations for both the objective function and the prevailing constraints evolutionary optimization has been employed to find the global extremas.

The most essential task in the optimization process is the formulation of the optimization model. This involves identification of all decision variables to be optimized, objective functions and related constraints as functions of decision variables, declaration of limits for decision variables, and expression of the optimization problem as a mathematical equation in a standard form so that it can be directly used by the optimization algorithm.

3.1 Parametric optimization of Electro-discharge machining

The experimental procedure is taken from the work of Thangadurai and Asha [26] where the authors evaluated the performance of electric discharge machining during machining of AA6061-wt.10% B4Cp metal matrix composite. The work piece material was A6061 wt. 10% B4Cp in the form of square bar having 18 mm x 18 mm x 84 axial length [26]. The composition of aluminium composite is 90 % of AA6061 aluminium and 10 % of Boron carbide composite particulate.

AA6061 – wt.10% B4Cp composite was machined using copper electrode of 14 mm diameter on ELECTRA PLUS EDM machine as shown in Figure. 10. Positive polarity was maintained for the work piece and negative polarity for the tool. Commercial grade kerosene was used as the dielectric fluid and impulse jet flushing was used to flush the eroded materials from the sparking zone [26].

Figure 10 : EDM machine set up [26]

To investigate the effect of machining parameters on material removal rate, tool wear rate and surface roughness, three independent machining parameters i.e. current, pulse on-time and pulse off-time were considered for experimentation. The experiments were designed by using Minitab version 16.0 (DOE).Response Surface Methodology (RSM) was used as a tool for mathematical modelling of Material Removal Rate (MRR),Tool Wear Rate (TWR) and Surface Roughness (Ra). RSM was employed to evaluate the relationship between the individual responses and the input machining parameters in the following functional form:

Objective function X = f (X_1, X_2, X_3)

Where X is the desired response and f (X_1, X_2, X_3) is the response function or response surface comprising of three machining parameters: current (X_1), pulse on-time (X_2) and pulse off-time (X_3).The approximation of X has been presented by fitting second-order polynomial regression equation i.e., quadratic equation in the form Equation 16:

$$Y = b_o + \sum_{i=n}^{n} b_i X_{iu} + \sum_{i=n}^{n} b_{ii} X_{iu}^2 + \sum_{i<y} b_{ij} X_{iu} X_{ju} \tag{16}$$

$Where:$

$Yu = corresponding\ response$

$Xiu = coded\ or\ uncoded\ values\ of\ ith\ machining\ parameters\ for\ uth\ experiment$

$n = number\ of\ machining\ parameters$

$bi, bii, bij = second\ order\ regression\ coefficients$

The experimental data required for development of response models have been collected by designing the experiment in Box-Behnken design (BBD) by varying each input parameter over three levels coded -1,0,+1. The levels and range of machining parameters selected in the study is tabulated in Table 1.

Table 1 : Levels and range of machining parameters

Variable	**A**	**B**	**C**
Level	Current (A)	Pulse on-time (μs)	Pulse off-time (μs)
-1	7.5	200	50
0	12.5	600	125
1	10	1000	200

The depth of cut has been kept constant at 1 mm throughout the experimentation. The experimental design consists of 17 runs as outlined in Table 2. Each run was performed by using a composite material size 18 mm x 18 mm x 84 mm [26].

Thangadurai and Asha [26] presented the mathematical modelling for three process responses namely MRR, TWR and Ra. These equations were formulated in uncoded or real units. However, in this thesis coded units have been used for the formulation of new response equations, which are further used in single and multi-objective optimization of process parameters.

Table 2 : Box Bekhen design for experiment on EDM

Run no.	Current (A)	Pulse on-time (μs)	Pulse off-time (μs)	MRR (g/min)	TWR(g/min)	Ra (μm)
1	7.5	600	200	0.0267	0.0041	5.769
2	10	600	125	0.0351	0.0063	6.674
3	12.5	600	200	0.0856	0.0063	7.342
4	7.5	600	50	0.0287	0.0043	5.234
5	10	1000	50	0.0411	0.0068	6.576
6	7.5	1000	125	0.0301	0.0037	5.785
7	12.5	200	125	0.0835	0.0052	7.235
8	10	200	50	0.0398	0.0052	6.382
9	10	600	125	0.0351	0.0062	6.659
10	7.5	200	125	0.0325	0.0041	5.745
11	12.5	600	50	0.0865	0.0077	7.523
12	10	600	125	0.0352	0.0062	6.554
13	10	1000	200	0.0498	0.0058	6.889
14	10	200	200	0.0322	0.0052	6.221
15	10	600	125	0.0386	0.0061	6.657
16	12.5	1000	125	0.0937	0.0079	7.749
17	10	600	125	0.0351	0.0058	6.554

The equations presented by Thangadurai and Asha [26] are presented by Equations 17-19.

$$MRR = 0.28022 - 0.054956 * A - 7.00604E-005 * B - 1.39833E-004 * C + 3.15000E-006 * A * B + 1.46667E-006 * A * C + 1.35833E-007 * B * C + 3.22240E-003 * A^2 + 2.49375E-008 * B^2 + 1.62667E-007 * C^2 \tag{17}$$

$$TWR = -6.79826E-003 + 1.95200E-003 * A - 2.50833E-006 * B + 1.65556E-005 * C + 7.75000E-007 * A * B - 1.60000E-006 * A * C - 8.33333E-009 * B * C - 8.36000E-005 * A^2 - 2.32813E-009 * B^2 + 4.44444E-010 * C^2 \tag{18}$$

$$Ra = 1.77526 + 0.47979 * A - 1.45712E-003 * B + 0.013889 * C + 1.18500E-004 * A * B - 9.54667E-004 * A * C + 3.95000E-006 * B * C - 3.28800E-003 * A^2 + 1.84062E-007 * B^2 - 2.34756E-005 * C^2 \tag{19}$$

3.2 Electro-chemical Machining

The optimization model for the electro-chemical machining process is formulated in the present work based on analysis given by Bhattacharya and Sorkhel [27] and Acharya et al. [31].

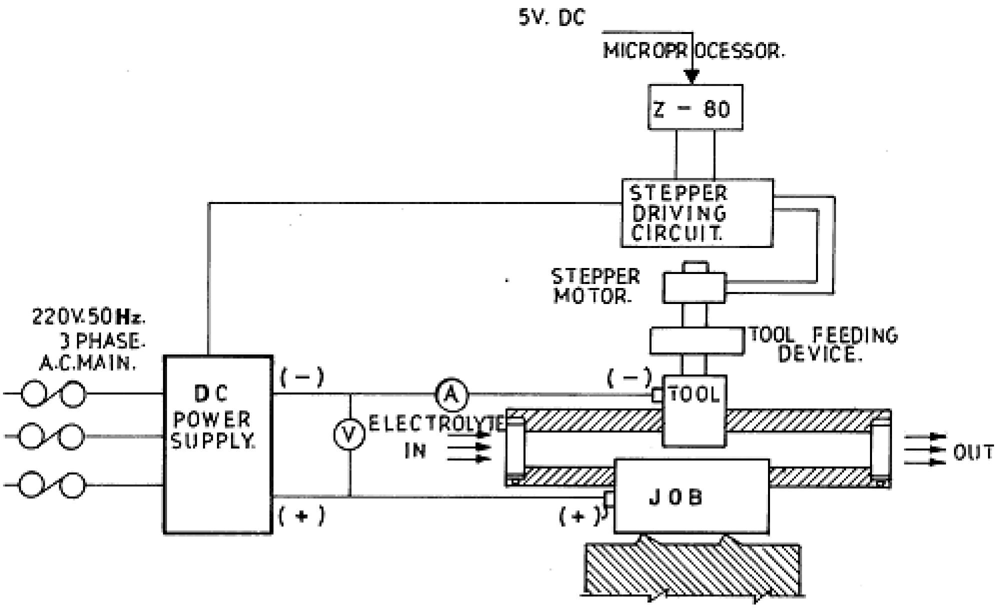

Figure 11 : The designed microprocessor based ECM set-up [27]

The experiment is taken from Bhattacharya and Sorkhel [27] which was carried on a developed ECM setup, as shown in Figure 11, having automatic tool feeding and controlled electrolyte flow. The electrical circuitry of the ECM set-up includes a DC power supply with electrical elements for short-circuit prevention, spark detection and auto-trip-ping operation of the ECM system. Closed-loop control electronic circuitry for securing controlled tool feed rates was designed and developed using a Z-80 microprocessor integrated with predesigned driver circuitry and a signal processor a potentiometer [27]. A milli-voltmeter and an A-to-D converter, for processing signals. thus generating various tool feed rates with the help of a stepper motor driving system to achieve constant current machining conditions. The feed-back signal consists of the change in the input AC that is supplied to the DC power supply module due to the fluctuation in the voltage drop across the gap between the tool and the work piece monitored by the three current transformers (CTs). These CTs arc placed across the three phases of the AC Input power line of the main ECM power supply unit. The system design has been made in such a way that the software-generated signals from an output port of the microprocessor will control the speed and direction of rotation of the stepper motor and thus in turn the tool feed rate [27].

A cylindrical solid brass tool of diameter 16 mm was used to carry out the experiments. The tool was insulated on the circumference to rectify the effect of stray current flow. Cylindrical work pieces of EN-8 steel having diameter 19 mm were used. NaCl was used as an electrolyte of varying concentrations, and its flow was based on cross flow methodology. The overcut considered for the analysis was the average radial overcut.

Table 4 displays the experimental scheme used by Minitab 16.0, where each input parameters is coded in five levels i.e. -2,-1, 0, +1+2 and a RSM based design was used with 7 centre points. The parametric search space for each input variable is tabulated in Table 3 along with their representing symbols. For the optimization problem the objective function and variable limits are defined by Equations 20-21. These equations have been converted into un-coded form before framing the modeling equations. For the optimization of parametric values Bhattacharya and Sorkhel [27] employed Gauss-Jordan Algorithm. The objective for multi response optimization was to maximize the material removal rate and to minimize the over cut while keeping the values of machining parameters within range.

Table 3 : Parametric levels for experiment on ECM

Parameters	Symbol	Levels				
		-2	-1	0	1	2
Electrolyte concentration (g/l)	x_1	15	30	45	60	75
Electrolyte flow rate (l/min)	x_2	10	11	12	13	14
Voltage (V)	x_3	10	15	20	25	30
Inter electrode gap (mm)	x_4	0.4	0.6	0.8	1.0	1.2

The mathematical relationship obtained for analysis of the various dominant machining parameters on the MRR and OC are given by Equations 20-21.

$$\begin{aligned} Z_{MRR}\,(g/\min) = {} & 1.19263 + 0.05688x_1 - 0.1359x_2 + 0.09215x_3 - 5.45671x_4 - 0.00004x_1^2 \\ & +0.01232x_2^2 + 0.00029x_3^2 - 0.36444x_4^2 - 0.00365x_1x_2 - 0.00067x_1x_3 \\ & +0.01407x_1x_4 - 0.01045x_2x_3 + 0.026505x_2x_4 + 0.09247x_3x_4 \end{aligned} \tag{20}$$

$$\begin{aligned} Z_{OC}\,(mm) = {} & -2.10705 + 0.01065x_1 + 0.31849x_2 + 0.00266x_3 + 0.48742x_4 - 0.0002x_1^2 \\ & -0.01223x_2^2 + 0.00011x_3^2 + 0.08501x_4^2 - 0.00040x_1x_2 - 0.00006x_1x_3 \\ & -0.00199x_1x_4 + 0.00044x_2x_3 - 0.02656x_2x_4 - 0.00781x_3x_4 \end{aligned} \tag{21}$$

Table 4 : Design of experiment for ECM

StdOrder	RunOrder	PtType	Blocks	x1	x2	x3	x4	MRR(g/min)	C (mm)
1	1	1	1	30	11	15	0.6	0.4895	0.255
2	2	1	1	60	11	15	0.6	0.77295	0.325
3	3	1	1	30	13	15	0.6	0.5097	0.27
4	4	1	1	60	13	15	0.6	0.827	0.315
5	5	1	1	30	11	25	0.6	0.685	0.3
6	6	1	1	60	11	25	0.6	0.9648	0.34
7	7	1	1	30	13	25	0.6	0.732	0.295
8	8	1	1	60	13	25	0.6	0.11635	0.345
9	9	1	1	30	11	15	1	0.298	0.315
10	10	1	1	60	11	15	1	0.49915	0.38
11	11	1	1	30	13	15	1	0.31655	0.31
12	12	1	1	60	13	15	1	0.5212	0.325
13	13	1	1	30	11	25	1	0.5952	0.32
14	14	1	1	60	11	25	1	0.8713	0.35
15	15	1	1	30	13	25	1	0.64475	0.325
16	16	1	1	60	13	25	1	0.9027	0.325
17	17	-1	1	15	12	20	0.8	0.24945	0.245
18	18	-1	1	75	12	20	0.8	0.97514	0.345
19	19	-1	1	45	10	20	0.8	0.5526	0.275
20	20	-1	1	45	14	20	0.8	0.84095	0.25
21	21	-1	1	45	12	10	0.8	0.33445	0.25
22	22	-1	1	45	12	30	0.8	1.01855	0.395
23	23	-1	1	45	12	20	0.4	0.92883	0.305
24	24	-1	1	45	12	20	1.2	0.2495	0.345
25	25	0	1	45	12	20	0.8	0.56525	0.295
26	26	0	1	45	12	20	0.8	0.7323	0.35
27	27	0	1	45	12	20	0.8	0.54172	0.32
28	28	0	1	45	12	20	0.8	0.5974	0.315
29	29	0	1	45	12	20	0.8	0.6367	0.295
30	30	0	1	45	12	20	0.8	0.65175	0.345
31	31	0	1	45	12	20	0.8	0.6458	0.34

Acharya et al. [31]considered three decision variables for the mathematical modelling which are tool feed rate f(mm/s), electrolyte flow velocity U(cm/s), and applied voltage (V).Multi-objective optimization was carried for the ECM process with maximization of the material removal rate, minimization of dimensional inaccuracy, and maximization of tool life as three conflicting objectives. Constraints were used in this model such as temperature constraint, passivity constraint, and choking constraint. The parametric optimization problem was solved by goal programming after linearizing the objective functions and constraint equations by using regression analysis.

Since the MRR is the product of tool feed rate and projected area the maximization of the tool feed rate would maximize the material removal rate (MRR) as the projected area is constant. Thus mathematically MRR can be expressed as Equation 22.

$$MRR_{max} = f_{max} \tag{22}$$

During an ECM process it is not possible to check the work piece dimensions unless a special techniques like Ultrasonic measurements are used. It is imperative to predetermine the control parameters to ensure the desired dimensional accuracy. Dimensional accuracy depends upon the difference in the inter-electrode gap at the inlet Y_i to outlet Y_o, which is given by Equation 23-24.

$$Y_o - Y_i = \left(\frac{K_o}{K_i} - 1 \right) \frac{K_i M_W \eta_i V}{\rho_W Z_W F f} \tag{23}$$

$$\frac{K_x}{K_i} = (1 - \alpha_x)^n \left[1 + \alpha (T_x - T_i) \right] \tag{24}$$

With K_o= K_x at the outlet. The objective of maximizing the dimensional accuracy is attained by minimizing the difference between the inter-electrode gap at the inlet Y_i to outlet Y_o Equation 23.

Maximization of tool life is ensured by minimizing the number of sparks per unit length N as given by the Equations 25-26.

$$N_{\min} = a + bE_i \frac{f^2}{VU} + c\frac{f}{V} \tag{25}$$

Where a, b and c are constants and

$$E_i = 1000 * \frac{A_a}{B} \left(\frac{\rho_w^2 Z_w F}{K_i M_w \eta_i} \right) \tag{26}$$

For the values of decision variables to be practical three constraints are considered for the modelsuch as Temperature, passivity and choking constraints. They are briefly described as follows [1].

3.2.1 Temperature constraint

To avoid boiling the electrolyte, the electrolyte temperature at the outlet should be less than the electrolyte boiling temperature. Mathematically this can be expressed as Equation 27.

$$T_i - \frac{1}{\alpha}\left[1 - \left(\frac{1 + S_k f^2}{\left(1-\alpha'_{\max}\right)^n U}\right)^{1/2}\right] \le T_b \qquad (27)$$

Where

$$S_k = \frac{2\alpha\gamma^2 L}{K_i \rho_e C_e J_{cn}}$$

$$\gamma = \frac{Z_w F \rho_w}{M_w \eta_i}$$

3.2.2 Passivity constraint

Oxygen evolved during electro-chemical machining forms an oxide film, which is the root cause of passivity. To avoid passivity, the thickness of the oxygen gas bubble layer must be greater than the passive layer thickness. Mathematically, this can be expressed as Equation 28.

$$G_t \frac{f\left(T_o + 273\right)}{U\alpha'_{\max}} \ge 1 \qquad (28)$$

Where

$$G_t = \frac{R\rho_f R_f L\gamma}{P_o t_p i}$$

3.2.3 Choking constraint

Hydrogen evolved at the cathode during the ECM process can choke the electrolyte flow. To avoid choking the electrolyte flow, the maximum thickness of the hydrogen bubble layer should be less than the equilibrium inter-electrode gap. Mathematically, it can be expressed as Equation 29.

$$\frac{H_t f^2\left(T_o + 273\right)}{VU\alpha'_{\max}\left(1-\alpha'_{\max}\right)^n\left[1+\alpha\left(T_o - T_i\right)\right]} \le 1 \qquad (29)$$

where

$$H_t = \frac{M_h R L \gamma^2}{Z_h P_o F K_i}$$

Acharya et al. [31] formulated the objective functions subjected to the constraints of temperature, passivity, and choking which were directly used by the optimization algorithm. These mathematical formulations are represented by the Equations 30-33.

Minimize

$$Z_1 = f^{0.381067} U^{-0.372623} V^{3.155414} e^{-3.128926} \quad \text{(30-a)}$$

$$Z_2 = f^{3.528345} U^{0.000742} V^{-2.52255} e^{0.391436} \quad \text{(30-b)}$$

$$Z_3 = f \quad \text{(30-c)}$$

where,

Z_1 is dimensional inaccuracy (mm), Z_2 is number of sparks per mm and Z_3 is the material; removal rate, f is tool feed rate (µm/s), U is the electrolyte flow elocity(cm/s), e is a constant 2.718

Subjected to:

- Temperature constraint:

$$1 - f^{2.133007} U^{-1.088937} V^{-0.351436} e^{0.321968} \geq 0 \quad (31)$$

- Passivity constraint

$$f^{-0.844369} U^{-2.526076} V^{1.546257} e^{12.57697} - 1 \geq 0 \quad (32)$$

- Choking constraint:

$$1 - f^{0.075213} U^{-2.488362} V^{0.240542} e^{11.75651} \geq 0 \quad (33)$$

Where the parameter bounds were defined as follows

$$8 \leq f \leq 200 \; (\mu m / s)$$
$$300 \leq U \leq 5000 (cm / s)$$
$$3 \leq V \leq 21 \; (V)$$

3.3 Electro-chemical Discharge Machining

This experiment is taken from [37] where parametric analysis on electro-chemical discharge machining of silicon nitride ceramics was carried out using steepest ascent method. In the experimental study, ECDM micro-drilling was performed on 20 x 20 mm and 5 mm thick silicon nitride ceramics. A stainless steel tool with a diameter of 400 nm was chosen for the experiment. The selection of the electrolyte for a micro-ECDM process is very much important because type and concentration determines the electro-chemical reaction. To carry out the experiment, aqueous NaOH salt solution was used for the electrolyte. The electrolyte concentration varied from 10 to 30 wt. % (e.g. 10-30 g NaOH salt per 100 ml of water). The flow of electrolyte was not considered because it removes the gas bubbles generated during machining operation, resulting in weak sparking and low material removal. Pulsed DC power supply was selected and experiments were carried out at five different voltage levels: 50 V, 54 V, 60 V, 66 V, and 70 V. The auxiliary electrode was made of stainless steel and larger than the cathode tool.

After selecting the tool, electrolyte, range of applied voltage and inter-electrode gap setting, the experiments were carried out using stagnant electrolyte and stationary tool. The machining operation was performed for 45 min. The weight of the job was measured with an electronic weighting machine (accuracy of 1×10^{-4} g), and the diameter of the machined micro-holes and the average thickness of the heat affected zone along the radial direction were measured at magnifications of 5X and 10X, respectively, with a measuring microscope (Olympus STM6).

To explore the multi-parametric combinations for the ECDM process on non-conducting ceramics, experiments were carried out according to a central composite second order rotatable design with 20 runs, 6 axial points and 6 centre points (see Table 6). MINITAB software was employed to determine the coefficients of mathematical modelling based upon response surface regression model. The applied voltage (V), electrolyte concentration(EC) and Inter-electrode gap(IEG) were considered as independent input parameters, while material removal rate (MRR), radial over-cut(ROC) and heat affected zone (HAZ) are the responses. The list of parameters with their corresponding low and high limits are tabulated in Table 5 with their corresponding variables.

Table 5 : List of parameters, corresponding variables, low and high limits [37]

Parameter	Variable name	Low limit	High limit
Applied voltage (V)	X1	50	70
Electrolyte concentration (wt %)	X2	10	30
Inter-electrode gap (mm)	X3	20	40

The relationship between the applied voltage, electrolyte concentration and inter electrode gap on the material removal rate, radial overcut and heat affected zone were derived using MINITAB and relevant experimental data [37]. The mathematical relationships are expressed by Equations 34-36. The machining parameters with their corresponding low and high limit are tabulated in Table 5.

$$MRR\,(mg/hr) = 4.96423 - 0.2041\,x_1 + 0.0986\,x_2 + 0.00851\,x_3 + 0.00249\,x_1^{\,2} - 0.00086\,x_2^{\,2} + 0.00039\,x_3^{\,2} - 0.00181\,x_1x_2 - 0.00104\,x_1x_3 + 0.00125\,x_2x_3 \tag{34}$$

$$ROC\,(mm) = 3.15622 - 0.8019\,x_1 - 0.07678\,x_2 - 0.00356\,x_3 + 0.00069\,x_1^{\,2} + 0.00048\,x_2^{\,2} + 0.00016\,x_3^{\,2} + 0.00072\,x_1x_2 - 0.00026\,x_1x_3 + 0.00041\,x_2x_3 \tag{35}$$

$$HAZ\,(mm) = 0.940335 - 0.019541\,x_1 - 0.028638\,x_2 - 0.003122\,x_3 + 0.000147\,x_1^{\,2} + 0.000242\,x_2^{\,2} + 0.000017\,x_3^{\,2} + 0.000251\,x_1x_2 - 0.000017\,x_1x_3 + 0.000106\,x_2x_3 \tag{36}$$

Table 6 : Design of experiment for ECDM

StdOrder	RunOrder	PtType	Blocks	A	B	C	MRR(mg/hr)	ROC(mm)	HAZ(mm)
1	1	1	1	54	14	24	0.6	0.2045	0.0987
2	2	1	1	66	14	24	1.03	0.269	0.1192
3	3	1	1	54	26	24	0.57	0.1416	0.0736
4	4	1	1	66	26	24	0.73	0.2476	0.103
5	5	1	1	54	14	36	0.53	0.202	0.0981
6	6	1	1	66	14	36	0.8	0.1663	0.0889
7	7	1	1	54	26	36	0.67	0.1362	0.061
8	8	1	1	66	26	36	0.69	0.2672	0.1153
9	9	-1	1	49.90924	20	30	0.42	0.0996	0.0543
10	10	-1	1	70.09076	20	30	1.2	0.3746	0.1264
11	11	-1	1	60	9.909243	30	0.55	0.2432	0.1013
12	12	-1	1	60	30.09076	30	0.4	0.1899	0.0983
13	13	-1	1	60	20	19.90924	0.67	0.1866	0.0923
14	14	-1	1	60	20	40.09076	0.53	0.1826	0.0623
15	15	0	1	60	20	30	0.4	0.1836	0.0673
16	16	0	1	60	20	30	0.93	0.2379	0.0764
17	17	0	1	60	20	30	0.53	0.1444	0.0998
18	18	0	1	60	20	30	0.53	0.1308	0.0805
19	19	0	1	60	20	30	0.67	0.1089	0.0746
20	20	0	1	60	20	30	0.57	0.159	0.0723

Chapter 4: Optimization of Constrained Design Problems

Engineering design of mechanical elements is described by very large numbers of variables, and it is imperative for the designer to specify appropriate values for these variables. Skilled designers often use their expert knowledge, experience, and judgment to specify these variables to design effective engineering elements. Because of the complexity and large size of a typical design task, even the most expert designers are unable to consider all the variables at the same time. Design optimization of mechanical elements is defined as the application of optimization algorithms and techniques to the problems in engineering design in order to help the designers in improving the system's performance, weight, reliability, and/or cost. Optimization methodologies are applied during the product development stage to ensure that the finished design will have the high performance, high reliability, low weight, and/or low cost. Alternatively, optimization methods can be applied to existing products to identify potential design improvements.

In this thesis three elements from the mechanical domain have been considered, which are Pressure Vessel Design [6], Welded Beam Design [6], and Tension Compression Spring Design [6]. The design problem associated with all the three elements considered are solved using evolutionary algorithms and a few results have also been compared with those of conventional techniques and other evolutionary algorithms.

4.1 Pressure vessel design

A cylindrical vessel is sealed at both ends by hemispherical heads as shown in Figure 12. The objective considered is to minimize the total cost, including the cost of the material, welding and forming. Four design variables namely: thickness of the shell (T_s), thickness of the head (T_h), inner radius (R) and the length of the cylindrical section (L) not including the head. The design vector is now defined as X=(x1, x2, x3, x4) = (T_s , T_h, R, L). Rao and Savsani[6] provided optimal solutions for pressure vessel design by considering practical values of T_s and T_h as integer multiples of 0.0625 inch(available thicknesses of rolled steel plates), and R and L as continuous.

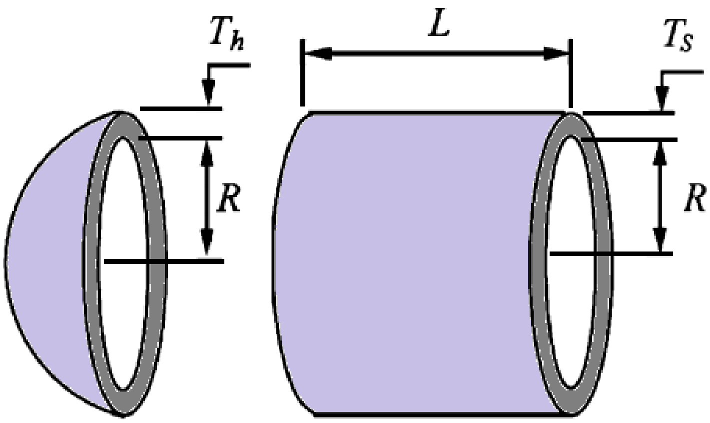

Figure 12 : Variables used in design of pressure vessel

However in this thesis values of T_s and T_h are also considered as continuous in the quest for global minimum and for the ease of programming of the optimizing algorithm. The best solution reported is f(X) =6059.714339 with X= (0.8125, 0.4375, 42.098446, 176.636596). The problem is presented by the Equations 37-41.

Minimize:

$$f(x) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 + 19.84x_1^2x_3 \quad (37)$$

Subject to:

$$g_1(x) = -x_1 + 0.0193x_3 \le 0 \quad (38)$$

$$g_2(x) = -x_2 + 0.00954x_3 \le 0 \quad (39)$$

$$g_3(x) = -\pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1{,}296{,}000 \le 0 \quad (40)$$

$$g_4(x) = x_4 - 240 \le 0 \quad (41)$$

Where,

$$0.1 \le x_1 \le 99, 0.1 \le x_2 \le 99, 10 \le x_3 \le 200, 10 \le x_4 \le 200$$

The above optimization problem was also solved by many researchers by using several optimization methods like branch and bound approach [38], Hybrid PSO-DE [46], Artificial Bee Colony (ABC) [47],an augmented Lagrangian Multiplier approach [39], Self adaptive penalty approach [40], Society and civilization algorithm [41], Ant colony algorithm [49], Evolutionary Strategy(ES) [42], Genetic Adaptive Search method (GeneAS) [50], Unified Particle Swarm Optimization (UPSO) [43], Co-evolutionary Differential Evolution (CoDE) [45], Co-evolutionary Particle Swarm Optimization (CPSO) [44] etc.

4.2 Welded beam design

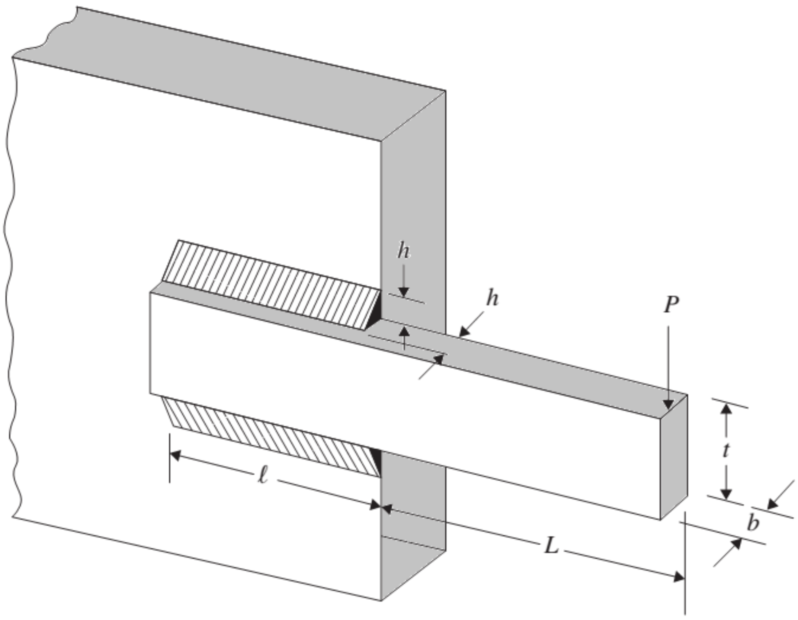

Figure 13 : Variables used in design of welded beam

This example is taken from Rao and Sivsani [6]. The objective is to design a welded beam at minimum cost. There are four design variables height of weld (h), length of weld (L), height of beam (t) and width of beam (b) as shown in Figure. 13. Design vector is defined as X=(x1, x2, x3, x4) = (h, L, t, b). Design is subjected to the constraints on shear stress (s), bending stress in the beam (r), buckling load on the bar (Pc), end deflection of the beam (d) and side constraints. The best value reported in the literature is f(X) =1.724852 with X= (0.205730, 3.470489, 9.036624, 0.205730). The problem is presented by the Equations 42-49.

Minimize:

$$f(x) = 1.10471 x_1^2 x_2 + 0.04811 x_3 x_4 (14.0 + x_2) \quad (42)$$

Subject to:

$$g_1(x) = \tau(x) - \tau_{\max} \le 0 \quad (43)$$

$$g_2(x) = \sigma(x) - \sigma_{\max} \le 0 \quad (44)$$

$$g_3(x) = x_1 - x_4 \le 0 \quad (45)$$

$$g_4(x) = 0.10471 x_1^2 + 0.04811 x_3 x_4 (14.0 + x_2) - 5.0 \le 0 \quad (46)$$

$$g_5(x) = 0.125 - x_1 \le 0 \quad (47)$$

$$g_6(x) = \delta(x) - \delta_{\max} \le 0 \quad (48)$$

$$g_7(x) = P - P_c(x) \le 0 \qquad (49)$$

Where,

$$\tau(x) = \sqrt{(\tau')^2 + 2\tau'\tau''\frac{x_2}{2R} + (\tau'')^2}, \tau' = \frac{P}{\sqrt{2}x_1x_2}, \tau'' = \frac{MR}{J}, M = p(L + \frac{x_2}{2})$$

$$R = \sqrt{\frac{x_2^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2}, J = 2\left[\sqrt{2}x_1x_2\left\{\frac{x_2^2}{12} + \left(\frac{x_1 + x_3}{2}\right)^2\right\}\right], \sigma(x) = \frac{6PL}{x_4x_3^2}$$

$$\delta(x) = \frac{4PL^3}{Ex_3^3x_4}, P_c(x) = \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2}\left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right),$$

$$P = 6{,}000 lb, L = 14 in, E = 30e6\ psi, G = 12E6\ psi,$$
$$\tau_{\max} = 13{,}600\ psi, \sigma_{\max} = 30{,}000\ psi, \delta_{\max} = 0.25 in$$

and,

$$0.1 \le x_1, x_4 \le 2.0; 0.1 \le x_2, x_3 \le 10.0$$

P_c is the bar buckling load, L is the length of the bar, E is the modulus of Elasticity, G is the modulus of rigidity, τ_{max} is the design shear stress of the weld, σ_{max} is the design normal stress of the weld, δ_{max} is the maximum beam bending stress.

This problem is solved by many researchers by using different optimization methods such as geometric programming [48], Hybrid PSO-DE [46], Artificial Bee Colony (ABC) [47], self adaptive penalty approach [40], society and civilization algorithm [41], Ant colony algorithm [49], Evolutionary Strategy(ES) [42], Unified Particle Swarm Optimization (UPSO) [43], Genetic Adaptive Search method (Gene-AS) [50], Co-evolutionary Particle Swarm Optimization (CPSO) [44], Co evolutionary Differential Evolution (CoDE) [45] etc.

4.3 Design of Tension Compression spring

This problem is taken from Rao and Savsani [6] which presents the minimization of the weight of a tension-compression spring as shown in Figure 14.The spring is subjected to constraints of surge frequency, minimum deflection, shear stress, limits on design variables and on outside diameter.

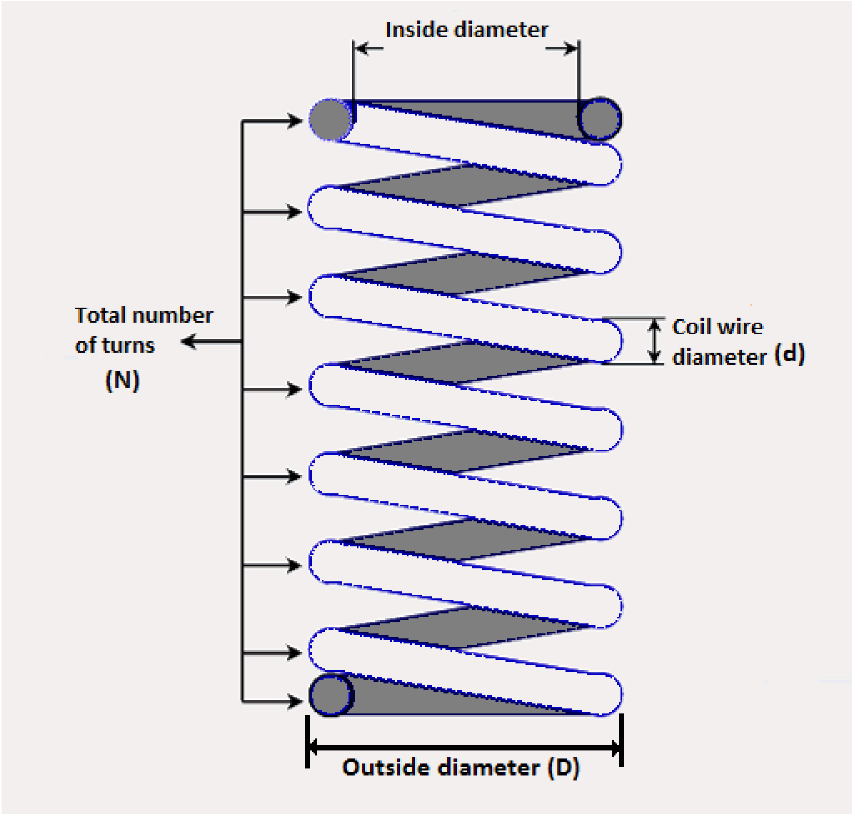

Figure 14 : Variables used in design of tension-compression spring

The design variables are the wire diameter (d), the mean coil diameter (D) and the number of active coils (N). Design vector is defined as X=(x1, x2, x3) = (d, D, N). The best result reported is f(X) =0.012665 with X= (0.051749, 0.358179, 11.203763). The problem is presented by the Equations 50-54

Minimize:

$$f(x) = (N+2)Dd^2 \tag{50}$$

Subject to:

$$g_1(x) = 1 - \frac{D^3 N}{7178 d^4} \le 0 \tag{51}$$

$$g_2(x) = \frac{4D^2 - dD}{12{,}566(Dd^3 - d^4)} + \frac{1}{5{,}108 d^2} - 1 \le 0 \tag{52}$$

$$g_3(x) = 1 - \frac{140.45 d}{D^2 N} \le 0 \tag{53}$$

$$g_4(x) = \frac{D+d}{1.5} - 1 \le 0 \tag{54}$$

Where

$$0.05 \le x_1 \le 2, 0.25 \le x_2 \le 1.3, 2 \le x_3 \le 15$$

This problem is solved by many researchers by using different optimization techniques such as self adaptive penalty approach [40], Hybrid PSO-DE [46], Ant colony algorithm [49], society and civilization algorithm [41], Evolutionary Strategy(ES) [42], Co-evolutionary Particle Swarm Optimization (CPSO) [44], Co-evolutionary Differential Evolution (CoDE) [45], Unified Particle Swarm Optimization (UPSO) [43], Artificial Bee Colony (ABC) [47] etc.

Chapter 5: An Improved Teaching Learning Based Optimization

The first proposal is the Bit string mutation, which was induced in the population generated at the end of every generation with a probability of 20%. The worst solutions at the end of the generation were now mutated in anticipation to escape the local optima. The second modification also proposed a similar methodology, but instead of mutating the solutions, fresh solutions were randomly generated which replaced the worst solutions in the population at the end of every generations. The Figure 16 displays the augmentation of these modifications with the original TLBO algorithm which is shown in Figure 15.
Both the modifications were separately coded in program, thus providing the liberty of user based execution of algorithm.

5.1 Demonstration of TLBO for Optimization

Step-string procedure for the demonstration of improvement in TLBO is given in this section. For demonstration purpose four variable Rastrigin function is used. The function is defined in Equation 55. Rastrigin function is a multimodal, separable and regular function.

$$f(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10 \tag{55}$$

The procedure is demonstrated as follows:

Step 1: Define the optimization problem and initialize the optimization parameters

$Initialize\ population\ size\ = 10$

$Number\ of\ generations = 20$

$Number\ of\ design\ variables\ = 4$

$Limits\ of\ design\ variables = -5.12 \leq x_i \leq 5.12$

Define optimization problem as:

Minimise $$f(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10 \tag{56}$$

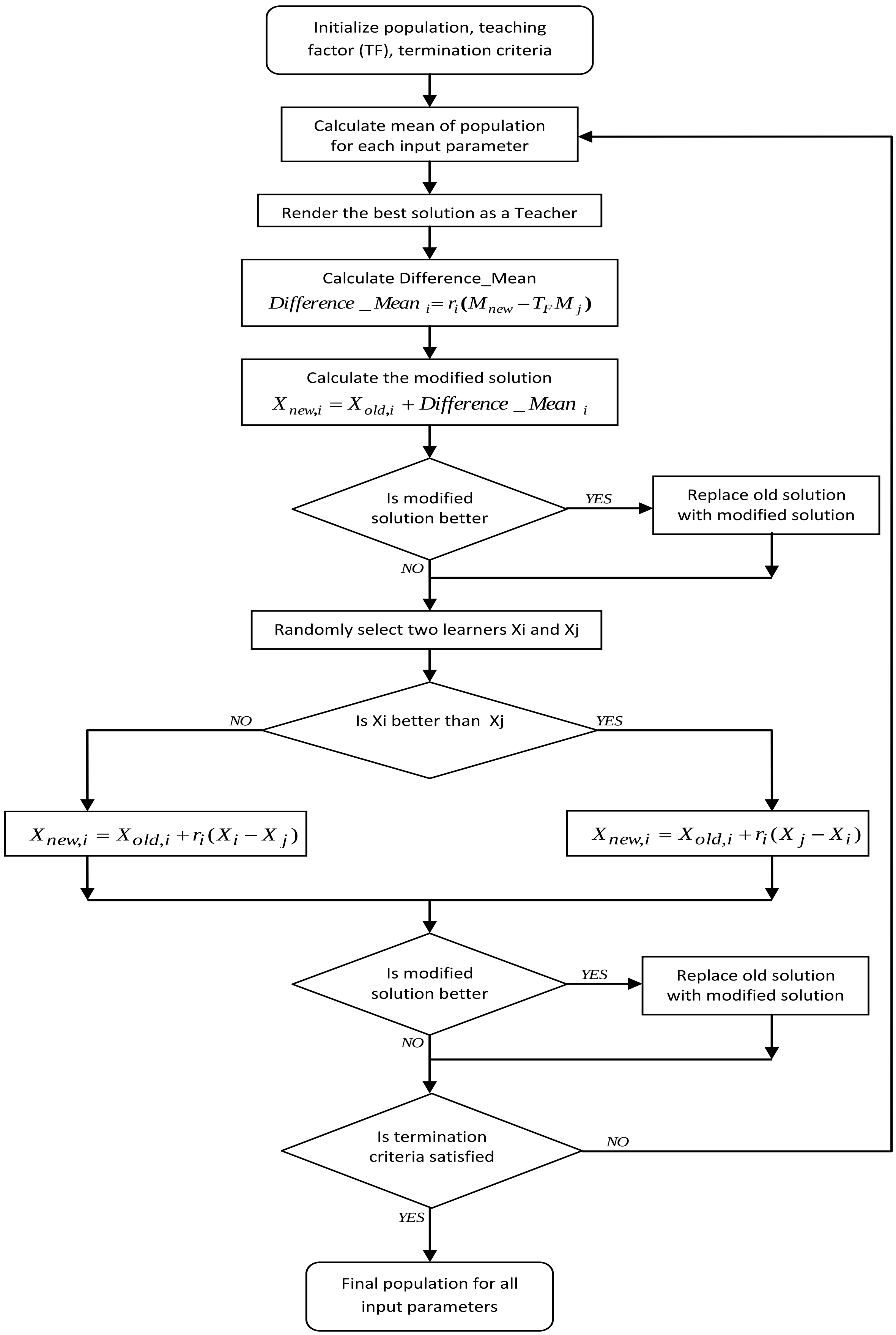

Figure 15 : Flow chart of TLBO

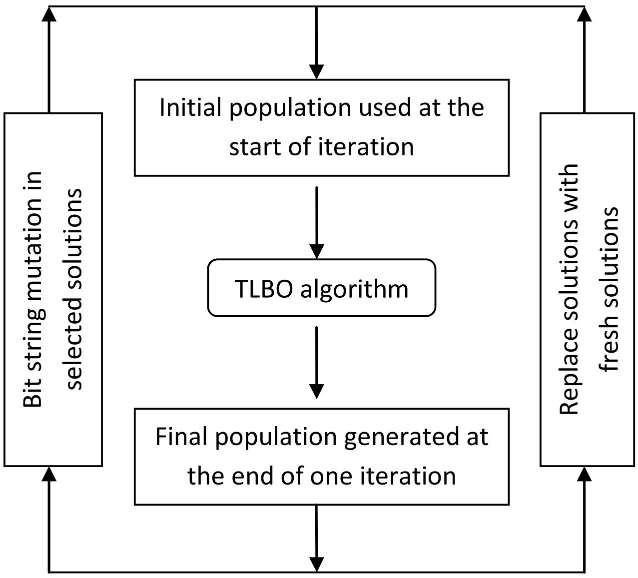

Figure 16 : Implementation of proposed modifications

Step 2: Generate the initial population

Generate random population according to the population size and the number of design variables. For TLBO, population size indicates the number of learners and the design variables indicate the subjects (i.e. courses) offered. This population is expressed as

$$initial\ \ population = \begin{bmatrix} x_{1,1} & x_{1,2} & . & . & x_{1,D} \\ x_{2,1} & x_{2,1} & . & . & x_{2,D} \\ . & . & . & . & . \\ . & . & . & . & . \\ x_{P_n,1} & x_{P_n,2} & . & . & x_{P_n,D} \end{bmatrix}$$

The initial population generated for each design variable in tabulated below along with the values of the objective function *f(x)* (see Table 7). Each design variable is treated as a subject in this algorithm.

Step 3: Teacher Phase

The mean of the population generated for each design variable is calculated and is presented in Equation 57

$$Mean\ (M_D) = [0.480872, 1.034997, 1.034997, 1.034997] \tag{57}$$

The best solution amongst the learners is treated as a teacher in the teachers phase. In this example the best solution is given by Learner 2 and is presented in the Equation 58

$$Teacher = X_{f(x)=min} = [1.920727, 1.044732, 1.044732, 1.044732] \quad (58)$$

Table 7 : Generation of initial population

Learner No.	subject1	subject2	subject3	subject4	f(x)
1	-1.54255	1.941589	1.941589	1.941589	35.33128
2	1.920727	1.044732	1.044732	1.044732	9.35573
3	1.185838	0.125134	0.125134	0.125134	16.33469
4	0.835175	0.586012	0.586012	0.586012	62.35254
5	-0.64475	-1.16085	-1.16085	-1.16085	34.66132
6	3.855287	2.826904	2.826904	2.826904	58.75556
7	-2.16617	0.098433	0.098433	0.098433	15.25123
8	0.656307	2.99512	2.99512	2.99512	42.90981
9	1.171594	0.440114	0.440114	0.440114	65.12544
10	-0.46274	1.452789	1.452789	1.452789	84.96288

The teacher now tries to shift the mean of the class according to the Equation 12. The value of teaching factor is randomly assumed as 1 or 2. This obtained difference is added to the current population to update its values using Equation 14. The modified solution and its corresponding objective function value are tabulated in Table 8.

Table 8 : Modification during teachers phase

Learner No.	mod_subject 1	mod_subject 2	mod_subject 3	mod_subject 4	F(x)
1	-1.22728	1.942047	1.948198	1.948202	23.152
2	3.26655	1.048465	1.049788	1.052821	26.50918
3	1.235617	0.125654	0.13029	0.131667	20.03148
4	0.84626	0.589744	0.586662	0.590076	61.51662
5	0.344104	-1.15512	-1.1518	-1.15262	32.5373
6	4.613988	2.827799	2.83327	2.830954	78.30764
7	-1.15655	0.107295	0.105853	0.100988	12.09622
8	0.724649	3.002285	2.998315	3.001278	39.12445
9	2.260716	0.449762	0.443671	0.442519	74.61957
10	0.95199	1.459824	1.460122	1.459131	66.79285

The next step is to accept all the new modified solutions which give a better function value. The old solutions are replaced by new ones in this case and the other solutions are carried forward as it is. The new population at the end of Teachers phase is now tabulated in Table 9.

Table 9 : End of teachers phase

Learner No.	T-subject1	T-subject2	T-subject3	T-subject4	F(x)-Teacher
1	-1.22728	1.942047	1.948198	1.948202	23.152
2	1.920727	1.044732	1.044732	1.044732	9.35573
3	1.185838	0.125134	0.125134	0.125134	16.33469
4	0.84626	0.589744	0.586662	0.590076	61.51662
5	0.344104	-1.15512	-1.1518	-1.15262	32.5373
6	3.855287	2.826904	2.826904	2.826904	58.75556
7	-1.15655	0.107295	0.105853	0.100988	12.09622
8	0.724649	3.002285	2.998315	3.001278	39.12445
9	1.171594	0.440114	0.440114	0.440114	65.12544
10	0.95199	1.459824	1.460122	1.459131	66.79285

Step 4: Learner Phase

As already explained in Chapter 1, the learners increase their knowledge by mutual interaction. Two learners from the population at the end of Teachers Phase are randomly selected and modified population is generated by using the Equation 15. The modified population is tabulated in Table 10.

Table 10 : Modification in learners phase

Learner No.	mod_subject 1	mod_subject 2	mod_subject 3	mod_subject 4	F(x)
1	-2.97945	0.97807	1.884598	0.995533	17.07411
2	1.920727	1.044732	1.044732	1.044732	9.35573
3	1.260443	-1.19173	-0.53432	-0.2299	48.93188
4	0.783307	0.562057	-0.61019	-0.92301	48.17058
5	0.344104	-1.15512	-1.1518	-1.15262	32.5373
6	3.657367	1.631821	1.910038	2.165568	63.13171
7	-2.58578	-0.77481	0.05883	-0.61769	52.76482
8	0.724649	3.002285	2.998315	3.001278	39.12445
9	1.171594	0.440114	0.440114	0.440114	65.12544
10	0.95199	1.459824	1.460122	1.459131	66.79285

The next step is similar to that of the teachers phase. Accept all the new modified solutions which give a better function value. The old solutions are replaced by new ones in this case and the other solutions are carried forward as it is. The new population at the end of Learners phase is now tabulated in Table 11.

Table 11 : End of learner phase

Learner No.	L-subject1	L-subject2	L-subject3	L-subject4	F(x)-Learner
1	-2.97945	0.97807	1.884598	0.995533	17.07411
2	1.920727	1.044732	1.044732	1.044732	9.35573
3	1.185838	0.125134	0.125134	0.125134	16.33469
4	0.783307	0.562057	-0.61019	-0.92301	48.17058
5	0.344104	-1.15512	-1.1518	-1.15262	32.5373
6	3.855287	2.826904	2.826904	2.826904	58.75556
7	-1.15655	0.107295	0.105853	0.100988	12.09622
8	0.724649	3.002285	2.998315	3.001278	39.12445
9	1.171594	0.440114	0.440114	0.440114	65.12544
10	0.95199	1.459824	1.460122	1.459131	66.79285

Step 5: Improvement in the algorithm

The first proposal is the Bit string mutation, which was induced in the population generated at the end of every generation with a probability of 20%. The worst solutions at the end of the generation were now mutated in anticipation to escape the local optima. The second modification also proposed a similar methodology, but instead of mutating the solutions, fresh solutions were randomly generated which replaced the worst solutions in the population at the end of every generations. The Figure 16 displays the augmentation of these modifications with the original TLBO algorithm. Improvement in the existing algorithm can be achieved by either Bit string mutation of the worst solutions in the population generated at the end of the Leaner's phase or by replacing the same by fresh solutions generated randomly within the search space. In this example Bit string mutation has been used to modify 20 % of the solutions which are regarded as the worst in the lot. The probability of the mutation is again taken as 20%. Bit string mutation is explained by an example as shown below.

The worst solution at the end of the generation is given by Equation 59 where the fitness value is evaluated at 66.79285.

$$Worst\ solution = X_{f(x)=max} = [0.95199, 1.459824, 1.460122, 1.044732] \tag{59}$$

Each value of decision variable is now converted in to binary form and represented in the form of a string as shown below. For each bit in this string mutation probability (0.2 in this case) is compared against a random number between 0 and 1. Based on this comparison bit flipping is done to get the new binary string.

For this example the values exist in decimal places, so in order to successfully convert them into binary, the value is multiplied by a suitable power of 10 for the sake of simplicity and ease of understanding. After bit string mutation has been completed the decimal value will be divided by the same power of 10 to get the modified decision variable value. Let us consider an exponent of 2 in this example.

$Let\ Decision\ variable\ value\ \ = 0.95$

$Mutiplying\ with\ an\ exponent\ of\ 5\ we\ get\ 0.95199 * 10^2 = 95$

$Converting\ to\ binary\ we\ get: \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 1 \quad 1$

$Let\ after\ mutation\ we\ get: \quad 1 \quad 0 \quad 1 \quad 1 \quad 1 \quad 0 \quad 1$

$Again\ converting\ to\ decimal\ we\ get\ value\ = 93$

$Final\ decision\ variable\ value\ after\ mutation\ = 0.93$

Similarly, all the mutated values of decision variables are evaluated and the new value replaces the existing solution in the final population. For the example considered so far, the values of decision variables and their corresponding function value are tabulated in Table 12. It can be easily pointed out that the learners 9 and 10 have undergone mutation at the end of the generation. Table 12 also serves as the initial population for the next generation. Inducing this mutation scheme greatly influences the algorithm to escape the local extrema and reach the near optimal global solutions.

Table 12 : Incorporation of proposed modification

Learner No.	subject1	subject2	subject3	subject4	f(x)
1	-2.97945	0.97807	1.884598	0.995533	17.07411
2	1.920727	1.044732	1.044732	1.044732	9.35573
3	1.185838	0.125134	0.125134	0.125134	16.33469
4	0.783307	0.562057	-0.61019	-0.92301	48.17058
5	0.344104	-1.15512	-1.1518	-1.15262	32.5373
6	3.855287	2.826904	2.826904	2.826904	58.75556
7	-1.15655	0.107295	0.105853	0.100988	12.09622
8	0.724649	3.002285	2.998315	3.001278	39.12445
9	1.5748	0.0016	0.5497	0.6961	55.02163
10	1.0096	1.4599	1.4603	1.4843	66.83056

A similar attempt can be replacing the worse solution at the end of each generation by fresh solutions which are randomly generated within the search space. Both these proposals of modifications have been induced in the coded algorithm, and comparison between the original algorithm and the proposed modifications in terms of performance have been thoroughly presented and discussed in the next chapter.

Step 6: Termination criterion

The algorithm halts when the termination criteria is satisfied else the algorithm restarts from step 3. The criterion used in this example is the maximum number of generations.
Detailed progress of the optimization algorithm for one generation depicting the modifications in Teachers phase and the Learner phase is presented in Table 13. It is clearly observed from Table 13 that the average value for f(x) and the best function value of the objective function decreases as the algorithm progresses from Teachers phase to the Learner phase in the same generation of the optimizing algorithm, and thus guarantee the convergence in the algorithm.

Table 13 : A generation of TLBO (4-variable)

subject1	subject2	subject3	subject4	f(x)	Mod subject1	Mod subject2	Mod subject3	Mod subject4	F(x)	T subject1	T subject2	T subject3
-2.97945	0.97807	1.8846	0.99553	17.0741	-2.90545	-0.33776	0.433068	-0.24227	54.3978	-2.97945	0.97807	1.884598
1.92073	1.04473	1.04473	1.04473	9.35573	2.06119	0.370659	0.658332	0.144785	41.7526	1.920727	1.044732	1.044732
1.04485	-0.07554	-0.86338	-0.83148	12.5989	1.083398	-0.81009	-1.92578	-1.60328	34.7994	1.044854	-0.07554	-0.86338
0.78331	0.56206	-0.61019	-0.92301	48.1706	0.834742	-1.26919	-2.23305	-2.01947	36.5102	0.834742	-1.26919	-2.23305
0.94528	-1.03433	-1.08634	-1.10845	8.85802	1.064042	-1.2078	-1.90336	-2.22399	29.4986	0.945283	-1.03433	-1.08634
4.0923	2.8205	0.2657	1.4973	65.3469	4.202157	1.134109	-0.23338	1.30803	53.617	4.202157	1.134109	-0.23338
-1.15655	0.1073	0.10585	0.10099	12.0962	-0.99189	-0.10139	-1.19468	-0.81058	17.9313	-1.15655	0.107295	0.105853
0.72465	3.00229	2.99832	3.00128	39.1245	0.778548	2.807806	1.67215	2.733704	59.1431	0.724649	3.002285	2.998315
2.07354	0.07209	0.65995	0.88831	25.3105	2.158264	-0.00427	0.280469	0.499055	41.442	2.073541	0.072094	0.659954
0.2276	1.1302	1.2682	0.7931	33.7934	0.349142	0.466701	0.519378	0.306988	69.7504	0.2276	1.1302	1.2682

T-subject4	F(x) Teacher	Mod subject1	Mod subject2	Mod subject3	Mod subject4	F(x)	L subject1	L subject2	L subject3	L subject4	F(x) Learner
0.995533	17.07411	-3.66128	0.946476	2.192312	1.052726	43.0638	-2.97945	0.97807	1.884598	0.995533	17.07411
1.044732	9.35573	1.920727	1.044732	1.044732	1.044732	9.35573	1.920727	1.044732	1.044732	1.044732	9.35573
-0.83148	12.59885	0.169702	-0.27485	-1.42856	-1.28349	51.6123	1.044854	-0.07554	-0.86338	-0.83148	12.59885
-2.01947	36.51019	0.917893	-5.00134	-2.58643	-3.66595	80.873	0.834742	-1.26919	-2.23305	-2.01947	36.51019
-1.10845	8.858024	0.062431	-0.37114	-0.4822	-0.03507	38.2117	0.945283	-1.03433	-1.08634	-1.10845	8.858024
1.30803	53.617	3.879334	0.149934	-0.11428	1.001077	25.4139	3.879334	0.149934	-0.11428	1.001077	25.41385
0.100988	12.09622	-1.15655	0.107295	0.105853	0.100988	12.0962	-1.15655	0.107295	0.105853	0.100988	12.09622
3.001278	39.12445	0.724649	3.002285	2.998315	3.001278	39.1245	0.724649	3.002285	2.998315	3.001278	39.12445
0.888306	25.31049	2.073541	0.072094	0.659954	0.888306	25.3105	2.073541	0.072094	0.659954	0.888306	25.31049
0.7931	33.79337	0.2276	1.1302	1.2682	0.7931	33.7934	0.2276	1.1302	1.2682	0.7931	33.79337

Chapter 6: Results and Discussions

It is observed from the literature that use of a particular optimization method or modification in a particular optimization method suits well to only a number of problems. However, the same method or modification may not work well for the other problems. In this work three unconstrained optimization problems are considered for the application of TLBO algorithm. All the problems considered for this purpose are taken from the production engineering domain and results are compared with those of previous published researches.

The proposal of a modification in any optimization algorithm requires a check of that modified algorithm for a wide variety of problems before drawing any general conclusion for the modification incorporated. To check the performance of the proposed modifications, six constrained problems are considered in this work. After attending the results for each optimization problem individually, a combined result is also drawn and presented at the end of the discussion to finalize on the impact of the modifications proposed.

6.1 Unconstrained Optimization Problems

Three non conventional machining processes are considered as unconstrained optimization problems from the production engineering domain namely Electro-Discharge Machining, Electro-Chemical Machining and Electro-Chemical Discharge Machining. An attempt to find the optimal parametric values for all the machining processes stated above has been made using the TLBO algorithm.

6.1.1 Optimization of Electro-Discharge Machining

The problem is taken from Thangadurai and Asha [26] and their work is completely described in Chapter 3. The experimental design was regenerated for 17 runs using Minitab version 16.0 (DOE) and the corresponding experimental responses are tabulated in Table 2 and have been directly used. Response Surface Methodology (RSM) was used to generate objective functions of Material Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness (Ra) which are presented by Equations 17-19.

Table 2 displays the Behnken design (BBD) used by Minitab 16.0, where each input parameter is coded in three levels i.e. -1, 0, +1. For the optimization problem the objective function and variable limits are defined by Equations17-19. These equations have been converted into uncoded form. The objective of multi response optimization is to maximize the material removal rate to minimize the tool wear rate and surface roughness while keeping the values of machining parameters within range.

Apart from the single objective functions considered for this problem, a combined function is also used to perform the multi-objective optimization for the EDM parameters. The function and the variable limits are given by Equation 60. Equal weights are considered for all the responses in this multi-objective optimization problem, and thus w_1= w_2= w_3 are all equal to (1/3).

$$Z_{Multi} = w_1 * \frac{Z_{Ra}}{Ra_{min}} + w_2 * \frac{Z_{TWR}}{TWR_{min}} - w_2 * \frac{Z_{MRR}}{MRR_{max}} \quad (60)$$

$Where:$

$7.5 < A < 10;\ and\ A{\sim}Current\ in\ ampere\ (A)$

$200 < B < 1000;\ and\ B{\sim}Pulse\ ontime\ in\ micro\ seconds(\mu s)$

$50 < C < 200;\ and\ C{\sim}\ Pulse\ offtime\ in\ micro\ seconds\ (\mu s)$

$Ra_{min}\ is\ the\ mininum\ value\ obtaied\ from\ single\ objective\ optimization\ of\ Z_{Ra}$

$TWR_{min} is\ the\ mininum\ value\ obtaied\ from\ single\ objective\ optimization\ of Z_{TWR}$

$MRR_{max} is\ the\ maximum\ value\ obtaied\ from\ single\ objective\ optimization\ of Z_{MRR}$

For the verification of mathematical models considered the analysis of variance was carried out and is tabulated in Tables 14-16. The explained variation i.e. R-square value obtained for MRR, TWR and Ra are 99.7%, 99.1% and 99.3% respectively. Based on this value it can be ascertained that the model is able to simulate the EDM process responses.

Table 14 : Analysis of variance for MRR-EDM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.00872	0.00872	0.000969	245.56	0
Linear	3	0.006777	0.006777	0.002259	572.51	0
Square	3	0.001837	0.001837	0.000612	155.19	0
Interaction	3	0.000106	0.000106	0.000035	8.99	0.008
Residual Error	7	0.000028	0.000028	0.000004		
Lack-of-Fit	3	0.000018	0.000018	0.000006	2.48	0.201
Pure Error	4	0.00001	0.00001	0.000002		
Total	16	0.008748				
R-Sq = 99.7%						

Table 15 : Analysis of variance for TWR-EDM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.000023	0.000023	0.000003	87.33	0
Linear	3	0.000018	0.000018	0.000006	206.96	0
Square	3	0.000002	0.000002	0.000001	20.83	0.001
Interaction	3	0.000003	0.000003	0.000001	34.21	0
Residual Error	7	0	0	0		
Lack-of-Fit	3	0	0	0	0.52	0.692
Pure Error	4	0	0	0		
Total	16	0.000023				
R-Sq = 99.1%						

Table 16 : Analysis of variance for Ra-EDM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	7.2921	7.2921	0.81023	108.48	0
Linear	3	6.97312	6.97312	2.32437	311.2	0
Square	3	0.07848	0.07848	0.02616	3.5	0.078
Interaction	3	0.2405	0.2405	0.08017	10.73	0.005
Residual Error	7	0.05228	0.05228	0.00747		
Lack-of-Fit	3	0.03777	0.03777	0.01259	3.47	0.13
Pure Error	4	0.01452	0.01452	0.00363		
Total	16	7.34438				
R-Sq = 99.3%						

In this thesis both single objective and multi-objective optimization have been performed using TLBO algorithm. For the single objective optimization for maximizing the MRR, minimizing the TWR and Ra. A population size of 10 was used. The Teaching Factor was considered as 1 for all the generations of the algorithm. The TLBO algorithm has given a maximum MRR of 0.1004 g/min, minimum TWR of 0.00337 g/min and minimum Ra of 5.2797 µm. The results are tabulated in Table 17.

Table 17 : Single objective results for EDM

Single objective optimization			
	MRR(g/min)	TWR (g/min)	Ra (µm)
Current (A)	12.5	7.5	7.5
Pulse on-time (µs)	1000	1000	1000
Pulse off-time (µs)	200	200	50
Optimal value	0.1004	0.00337	5.2797

For the multi-objective optimization the combined function has been used. It has already been established that these functions always gives compromising results by satisfying all the objectives. In our current study TLBO has also provided compromising solution for the combined objective function. Equal weights have been assumed in the combined objective function giving equal significance to all the process criteria. The minimum value obtained for the combined function is 0.59437, which corresponds to MRR of 0.03571 g/min,TWR of 0.003377 g/min, and Ra of 6.0012 μm have been tabulated in Table 18.

Table 18 : Multi-objective results for EDM

Multi-objective optimization		
	Numerical Opt. of RSM [26]	TLBO
Current (A)	12.5	7.5
Pulse on-time (μs)	200	1000
Pulse off-time (μs)	200	200
Optimal value	-	0.59437
MRR (g/min)	0.079265	0.03571
TWR (g/min)	0.00489051	0.003377
Ra (μm)	6.8812	6.0012

Thangadurai and Asha[26] employed Numerical Optimization techniques of RSM for multi response material removal rate, tool wear rate and surface roughness optimization. It is clearly seen that the results obtained by them are quite different from those obtained by TLBO technique. The values for TWR and Ra are better in the latter case, while the MRR value is found to have decreased. The former combination can be achieved by altering the relative weights assigned to the responses.

6.1.2 Optimization of Electro-Chemical Machining

Parametric optimization of ECM has been carried out by many researchers using different optimization techniques, however to check for any scope of further improvement TLBO has been applied to both single and multi-objective optimization of parameters. A similar attempt has been done by Rao and Kalyankar [17] where an individual attempt was made on both the objective functions.

The problem is taken from Bhattacharya and Sorkhel [27] and their work is completely described in Chapter 3. The experimental design was regenerated for 31 runs using Minitab version 16.0 (DOE) and the corresponding experimental responses are tabulated in Table 4 and have been directly used. Response Surface Methodology (RSM) was used to generate objective functions of Material Removal Rate (MRR) and Over cut (OC) which are presented by Equations 20-21.

Apart from the single object functions considered for this problem, a combined function is also used to perform the multi-objective optimization for the EDM parameters. The function and the variable limits are given by Equation 61. Equal weights are considered for all the responses in this multi-objective optimization problem, and thus w_1= w_2= w_3 are all equal to (1/3).

$$Z_{Multi} = w_1 * \frac{Z_{OC}}{OC_{min}} - w_2 * \frac{Z_{MRR}}{MRR_{max}} \tag{61}$$

$Where:$

$15 < x1 < 75;\ and\ x1 \sim Electrolyte\ concentration\ (g/l)$

$10 < x2 < 14;\ and\ x2 \sim Electrolyte\ flow\ rate\ (l/min)$

$10 < x3 < 30;\ and\ x3 \sim\ Applied\ voltage\ (V)$

$0.4 < x4 < 1.2;\ and\ x4 \sim\ inter\ electrode\ gap\ (mm)$

$OC_{min}\ is\ the\ mininum\ value\ obtaied\ from\ single\ objective\ optimization\ of\ Z_{OC}$

$MRR_{max} is\ the\ maximum\ value\ obtaied\ from\ single\ objective\ optimization\ of Z_{MRR}$

For the verification of mathematical models considered the analysis of variance was carried out and is tabulated in Tables 19-20 The explained variation i.e. R-square value obtained for MRR and OC are 65.0% and 74.7% respectively. Based on this value it can be ascertained that the model is able to simulate the ECM process responses.

Table 19 : Analysis of variance for MRR-ECM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	14	1.08047	1.08047	0.077176	2.12	0.076
Linear	4	0.72184	0.18477	0.046192	1.27	0.323
Square	4	0.01578	0.01578	0.003946	0.11	0.978
Interaction	6	0.34285	0.34285	0.057141	1.57	0.22
Residual Error	16	0.58267	0.58267	0.036417		
Lack-of-Fit	10	0.55861	0.55861	0.055861	13.93	0.002
Pure Error	6	0.02406	0.02406	0.004011		
Total	30	1.66314				
R-Sq = 65.0%						

Table 20 : Analysis of variance for OC-ECM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	14	0.030243	0.030243	0.00216	3.37	0.011
Linear	4	0.021587	0.021587	0.005397	8.42	0.001
Square	4	0.005671	0.005671	0.001418	2.21	0.114
Interaction	6	0.002984	0.002984	0.000497	0.78	0.6
Residual Error	16	0.010257	0.010257	0.000641		
Lack-of-Fit	10	0.007115	0.007115	0.000711	1.36	0.367
Pure Error	6	0.003143	0.003143	0.000524		
Total	30	0.0405				
R-Sq = 74.7%						

In this thesis both single objective and multi-objective optimization have been performed using TLBO algorithm. For the single objective optimization for maximizing the MRR, minimizing the OC a population size of 10 was used. The Teaching Factor was considered as 1 for all the generations of the algorithm. The TLBO algorithm has given a maximum MRR of 1.4551 g/min and minimum OC of 0.0818 mm. The results are tabulated in Table 21. It is to be noted that the optimal value of OC is reported as 0.0818 mm, which is better than the result obtained by Rao and Kalyankar [17].

Table 21 : Single objective results for ECM

Single objective optimization		
	MRR (g/min)	OC (mm)
Electrolyte concentration (g/l)	75	15
Flow rate (l/min)	10	10
Voltage (V)	30	10
Inter electrode gap (mm)	1.2	0.4
Optimal value	1.4551	0.0818

For the multi-objective optimization the combined function has been used. It has already been established that these functions always gives compromising results by satisfying all the objectives. In our current study TLBO has also provided compromising solution for the combined objective function. Equal weights have been assumed in the combined objective function giving equal significance to all the process criteria.

Table 22 : Multi-objective results for ECM

Multi-objective optimization		
	ABC[13]	TLBO
Electrolyte concentration (g/l)	15	15
Flow rate (l/min)	10	10
Voltage (V)	10	10
Inter electrode gap (mm)	0.4	0.4
Optimal value	0.3488	0.3488
MRR (g/min)	0.4408	0.4408
OC (mm)	0.0818	0.0818
Iterations used	100	20

The minimum value obtained for the combined function is 0.3488, which corresponds to MRR of 0.4408 g/min and OC of 0.0818 mm have been tabulated in Table 22. The results obtained by ABC algorithm is similar to that obtained by TLBO, but the number of generation used is five times less than that used by ABC.

The modified TLBO is now applied to all the three objective functions derived from the experimental data of ECM given by Equations 20-21 and Equation 61, and a comparative study has been done between the proposed modifications and original TLBO. To quantify the comparison the algorithm is run for a fixed number of generations and normalised deviations are calculated between already published results and best solution within the final population generated by the algorithm. This normalised deviation is calculated by calculated by dividing the standard deviation value from the published optimal value for the current optimization, the algorithm is run for 20 times with a different seed value of the random number.

Maximization of MRR

The results obtained from the single objective optimization of Equation 20 have been solved using the original TLBO and the modifications suggested in the previous chapter. The calculated values are tabulated in Table 33. The tabulated data is also presented graphically for easy analysis in Figure 17.

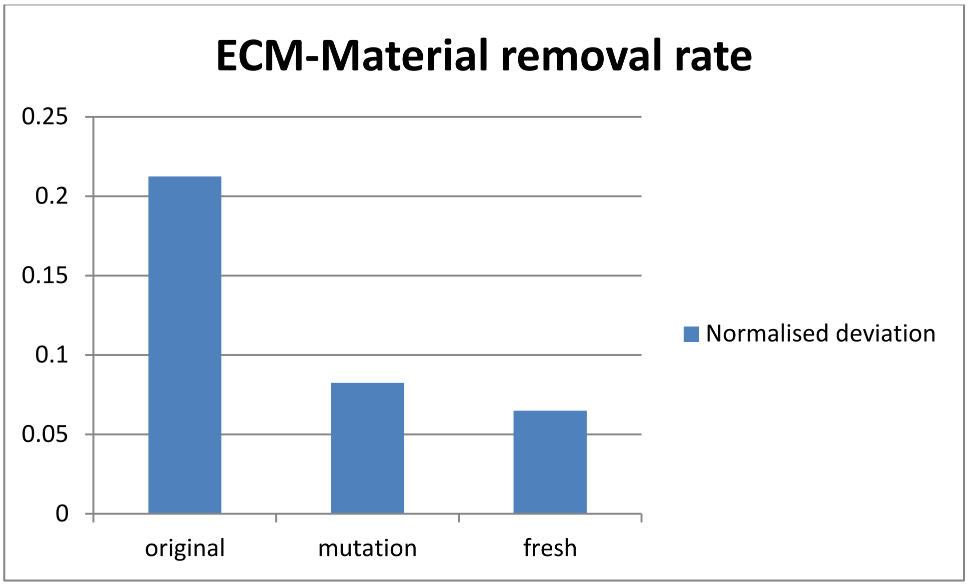

Figure 17 : Comparison graph for ECM-MRR

On comparative analysis of the table and the graph for the maximization of MRR, it is found that the average normalised standard deviations for original TLBO algorithm is 0.212543, Mutation based TLBO is 0.0.82417 and Replacing worst solutions with fresh ones gives 0.064981. Contrary to the results found so far Mutation based TLBO has not performed better than its competitors in reaching the global optimal solution in the given number of iterations with zero normalised standard deviations. Instead the scheme of replacement by fresh solutions has given better results for such kind of optimization problem. However the Mutation scheme has performed better than the original TLBO algorithm.

Minimization of radial overcut

The results obtained from the single objective optimization for minimizing the overcut are given in Equation 30 which is subjected to constraints Equations 31-33 .The problem has been solved using the original TLBO and the modifications suggested in the previous chapter. The calculated values are tabulated in Table 34. The tabulated data is also presented graphically for easy analysis in Figure 18.

On comparative analysis of the table and the graph for the minimization of OC, it is found that the average normalised standard deviations for original TLBO algorithm is 0.09662, Mutation based TLBO is 4.89E-06 and Replacing worst solutions with fresh ones gives 0.031149.

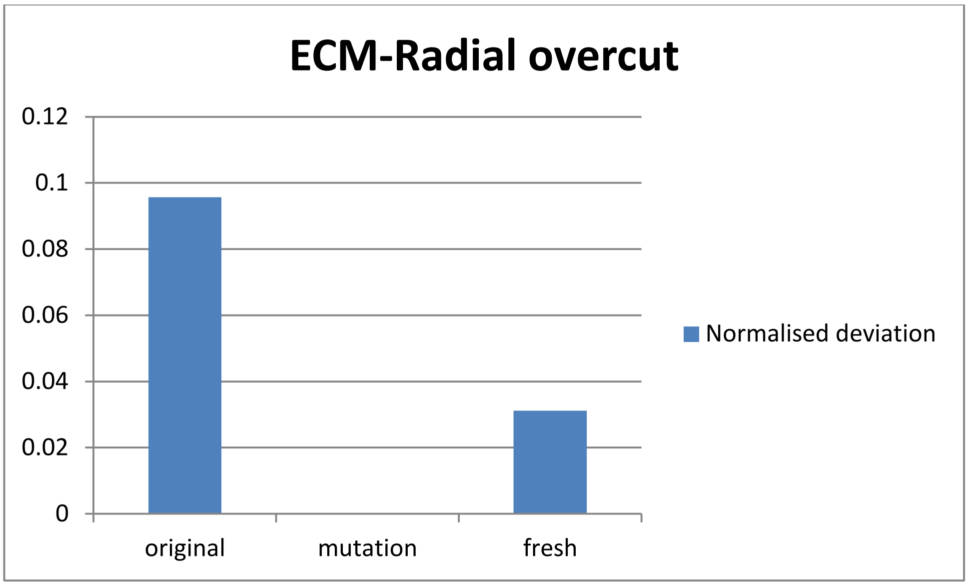

Figure 18 : Comparison graph for ECM-OC

It is again evident that Mutation based TLBO has performed better than its competitors in reaching the global optimal solution in the given number of iterations with zero normalised standard deviation. However for this problem it is seen that the next winner is the scheme of replacement by fresh solutions having less deviation followed by the original TLBO algorithm.

Multi-objective optimization of ECM process

The optimization was also carried for the combined function represented by Equation 61. where both the objectives of maximizing the MRR and minimising the OC were simultaneously considered.

On comparative analysis of the table and the graph (Figure 19) for this multi-objective problem, it is found that the average normalised standard deviations for original TLBO algorithm is 0.476929, Mutation based TLBO is 6.79E-05 and Replacing worst solutions with fresh ones gives 6.79E-05. In this particular case it is found that Mutation based TLBO and the scheme of replacement by fresh solutions have performed better than original TLBO in reaching the global optimal solution in the given number of iterations with zero normalised standard deviation.

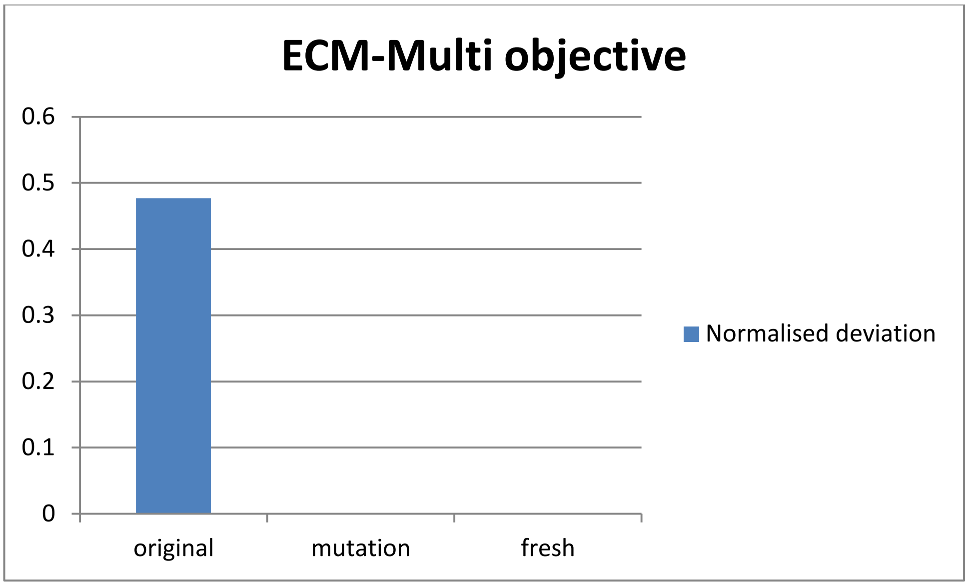

Figure 19 : Comparison graph for ECM-multi-objective

6.1.3 Optimization of Electro-chemical Discharge Machining

Parametric optimization of ECDM has been carried out by many researchers using different optimization techniques, however to check for any scope of further improvement TLBO has been applied to both single and multi-objective optimization of parameters. A similar attempt has been done by Rao and Kalyankar [17] where an individual attempt was made on all the objective functions.

This experiment is taken from Sarkar et al.[37] where parametric analysis on electro-chemical discharge machining of silicon nitride ceramics was carried out using steepest ascent method. The details of this experiment have been thoroughly visited in Chapter 3.The equations representing the objective functions are presented by Equations 30-32. Apart from the single object functions considered for this problem, a combined function is also used to perform the multi-objective optimization for the EDM parameters. The function and the variable limits are given by Equation 57 and the combined objective function used for the multi-objective optimization is presented by Equation 57.

$$Min.\ Z = w_1 * ROC / ROC_{\min} + w_2 * HAZ / HAZ_{\min} - w_3 * MRR / MRR_{\max} \quad (62)$$

Where *MRR*, *ROC* and *HAZ* are the RSM based equations from Equations 30-32 respectively, MRR_{max}, ROC_{min} and HAZ_{min} are the optimized maximum, minimum and minimum values of MRR, ROC and HAZ respectively calculated from single objective optimization. w_1, w_2, w_3 are the weights assigned to ROC, HAZ and MRR respectively.

Samanta and Chakraborty [13] had considered equal weights for all three responses, and thus $w_1 = w_2 = w_3$ are all equal to 1/3).

Table 23 : Analysis of variance for MRR-ECDM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.58663	0.58663	0.06518	2.82	0.061
Linear	3	0.39065	0.39065	0.13022	5.63	0.016
Square	3	0.13473	0.13473	0.04491	1.94	0.187
Interaction	3	0.06125	0.06125	0.02042	0.88	0.482
Residual Error	10	0.23115	0.23115	0.02312		
Lack-of-Fit	5	0.0668	0.0668	0.01336	0.41	0.827
Pure Error	5	0.16435	0.16435	0.03287		
Total	19	0.81778				
R-Sq = 71.7%						

Table 24 : Analysis of Variance for ROC-ECDM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.06081	0.06081	0.006757	3.19	0.042
Linear	3	0.040949	0.040949	0.01365	6.44	0.011
Square	3	0.011953	0.011953	0.003984	1.88	0.197
Interaction	3	0.007907	0.007907	0.002636	1.24	0.345
Residual Error	10	0.02118	0.02118	0.002118		
Lack-of-Fit	5	0.01085	0.01085	0.00217	1.05	0.479
Pure Error	5	0.01033	0.01033	0.002066		
Total	19	0.08199				
R-Sq = 74.2%						

Table 25 : Analysis of Variance for HAZ-ECDM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	0.006272	0.006272	0.000697	4.4	0.015
Linear	3	0.004151	0.004151	0.001384	8.75	0.004
Square	3	0.001346	0.001346	0.000449	2.84	0.092
Interaction	3	0.000775	0.000775	0.000258	1.63	0.243
Residual Error	10	0.001582	0.001582	0.000158		
Lack-of-Fit	5	0.000941	0.000941	0.000188	1.47	0.342
Pure Error	5	0.000641	0.000641	0.000128		
Total	19	0.007854				
R-Sq = 79.9%						

Analysis of variance is carried out for all responses and a second order model is found to be fit (see Tables 23-25). The coefficient of determination (R^2) for MRR, ROC, and HAZ are 71.7%, 74.2% and 79.9% respectively. Hence, the developed mathematical models which link the various machining parameters with MRR ROC and HAZ can adequately be represented through the response surface methodology.

Table 26 : Algorithmic parameters for Genetic algorithm and Simulated Annealing

ABC [13]	GA:
Swarm size: 10	Population size: 60
Maximum no. of generations: 100	Maximum Number of generations; 100
Number of employed bees: 50% of swarm size	Selection function: stochastic uniform
	Elite count: 2
Number of onlooker bees: 50% of swarm size	Crossover fraction: 0.8
	Crossover function: scattered
Number of scouts per cycle: 1	Mutation fraction: 0.2
Number of cycles: 2000	Mutation function: Gaussian
Number of parameters: 6	**Number of parameters: 8**

SA:	TLBO
Start point: origin	Population size: 10
Maximum Number of generations: 100	Maximum Number of generations: 20
Annealing function: fast annealing	Teaching factor: 2
Re-annealing interval: 100	
Temperature update function: logarithmic	
Initial temperature: 100	
Acceptance probability function: SA acceptance	
Number of parameters: 7	**Number of parameters: 3**

Optimization of process parameters is presented using four different techniques namely, GA, SA, ABC and TLBO and the results are compared with those obtained by past research. Both single objective and multi-objective optimization was performed considering the experimental data and mathematical modeling of past researchers. Optimization toolbox in Matlab 7.0 was used to generate results by Genetic algorithm and Simulated Annealing algorithm optimization techniques whereas coding of both the Artificial Bee Colony algorithm and Teaching Learning based Optimization algorithm were developed in Matlab 7.0 .The final tuning of their controlling parameters for easy convergence is enlisted in Table 26.

Single objective optimization was performed using four different evolutionary optimization methods namely Genetic algorithm, Simulated Annealing algorithm, Artificial Bee Colony algorithm and Teaching Learning based Optimization algorithm with intent to maximize MRR (5), minimize ROC (6) and minimize HAZ (7). The upper and lower limits specified in Table 5 were used as variable boundaries for applied voltage, electrolyte concentration and inter-electrode gap.

For the parameter values of $X_1 = 70$, $X_2 = 20$ *and* $X_3=20$[13], the optimal value of MRR is stated as 1.62603 mg/hr [13] using ABC algorithm whereas their use in the (5) yields a MRR value of 1.3372 mg/hr. This was earlier pointed out and an improved solution was provided [17]. Table 27 resurrects the optimal MRR value as obtained by Samantha and Chakraborthy[13] and successfully displays the competency of TLBO algorithm [18] with GA, SA and ABC algorithms by arriving at MRR value of 1.62603 mg/hr instead of 1.5902 mg/hr as suggested by Rao and Kalyankar[17].

Table 27 : Results of single objective optimization-ECDM

Response	Steepest ascent [37]	ABC Algorithm [13]	Genetic	Simulated annealing	TLBO
MRR(mg/hr)	1.24453	1.3372	1.6167	1.616	1.626
	X_1=70	X_1=70	X_1=70.09	X_1=70.09	X_1=70
	X_2=18	X_2=20	X_2=9.9	X_2=9.9	X_2=10
	X_3=27	X_3=20	X_3=19.9	X_3=19.9	X_3=20
ROC(mm)	0.11138	0.05912	0.0591	0.0591	0.0591
	X_1=50	X_1=50	X_1=49.91	X_1=49.90	X_1=50
	X_2=24	X_2=30	X_2=30.08	X_2=30.08	X_2=30
	X_3=30	X_3=20	X_3=19.91	X_3=19.91	X_3=20
HAZ (mm)	0.055874	0.05409	0.055	0.055	0.0541
	X_1=50	X_1=50	X_1=49.9	X_1=49.91	X_1=50
	X_2=22	X_2=24.5	X_2=24.65	X_2=24.65	X_2=25
	X_3=39	X_3=40	X_3=39.61	X_3=39.61	X_3=38

For the multi-objective optimization of the responses for the ECDM process, a combined objective function was developed considering all the three models simultaneously. The model used by Samantha and Chakraborthy is given by (12). The multi-objective optimization of ECDM process and comparison of results with those of ABC algorithm is presented in Table 28. The minimum objective function value for the multi-objective optimization is found to be 0.5844 which is similar to the results of Samanta and Chakraborty [13] and contrary to those of Rao and Kalyankar [17]. The values of MRR, ROC and HAZ also tally with the previously established results of Samanta and Chakraborty [13] using ABC algorithm.

Table 28 : Results of multi objective optimization-ECDM

Parameters and function	ABCalgorithm[13]	TLBOalgorithm
Applied voltage (V)	50	50
Electrolyte concentration (wt %)	30	30
Inter-electrode gap (mm)	20	20
MRR (mg/hr)	0.4860	0.4866
ROC (mm)	0.0591	0.0591
HAZ (mm)	0.0569	0.0569
Combined objective function value	0.5843	0.5844
Number of iterations	100	20

The use of the combined objective function gives satisfactory multi-objective results for each of the objective function. In this case also TLBO has proven to be competent with the ABC algorithm by arriving at the previously established result of Samanta and Chakraborty [13] in less number of iterations. In addition, TLBO requires less number of parameters to be controlled as compared to ABC. The number of functional evaluations and computational burden is much less in case of TLBO. Importantly, TLBO is easy to understand and implement because it mimics a simple phenomenon whereas ABC simulates complex physical process of collection of honey by the bees.

6.2 Constrained Optimization Problems

Like other optimization algorithms (e.g. PSO, ABC, ACO, etc.), TLBO algorithm do not have any special mechanism to handle the constraints. For the constrained optimization problems it is necessary to incorporate a constraint handling technique with the TLBO algorithm even though the algorithm has its own exploration and exploitation powers. In this thesis, a penalty term is introduced within the objective function to handle the constraints within the TLBO algorithm. During a constrain violation this penalty term is assigned a large number which makes the solution worst in itself. Consequently this worst solution is rejected by the algorithm in further iterations.

The modified TLBO is now applied to five constrained problems of mechanical domain, and a comparative study has been done between the proposed modifications and original TLBO. To quantify the comparison the algorithm is run for a fixed number of generations and normalised deviations are calculated between already published results and best solution within the final population generated by the algorithm. This normalised deviation is calculated by calculated by dividing the standard deviation value from the published optimal value for the current optimization problem for each of the examples considered in this thesis, the algorithm is run for 20 times with a different seed value of the random number. The optimization problems have been thoroughly discussed in the previous chapters. The results obtained are tabulated and discussed in terms of performance.

6.2.1 Pressure vessel design

The results obtained from the single objective optimization of Equation 33 subjected to constraints represented by Equations 34-37 have been solved using the original TLBO and the modifications suggested in the previous chapter. The calculated values are tabulated in Table 31. The tabulated data is also presented graphically for easy analysis in Figure 20.

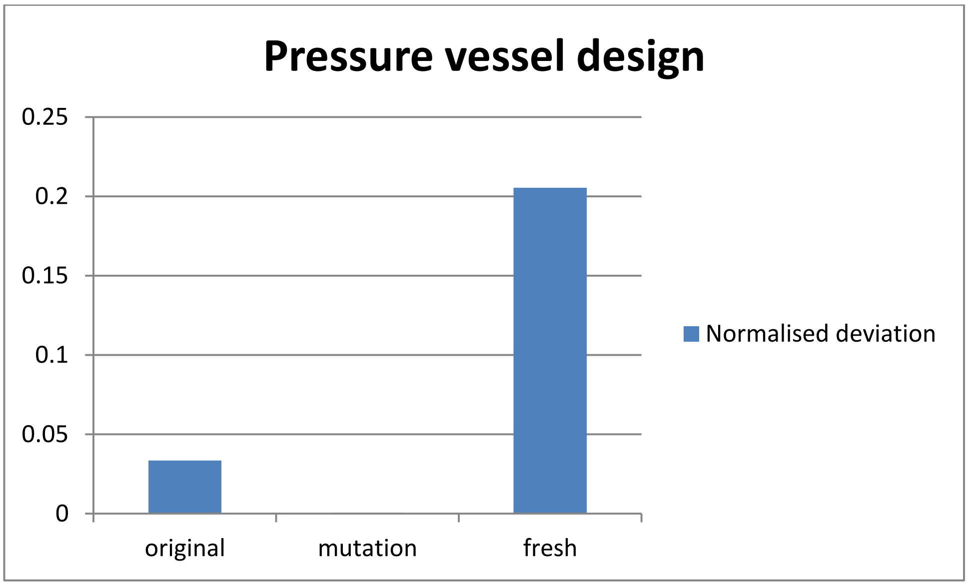

Figure 20 : Comparison graph for pressure vessel design

On comparative analysis of the table and the graph for the design of pressure vessel, it is found that the average normalised standard deviations for original TLBO algorithm is 0.03341,Mutation based TLBO is 0.000445 and Replacing worst solutions with fresh ones gives 0.205302. It is quite evident that Mutation based TLBO has performed better than its competitors in reaching the global optimal solution in the given number of iterations with zero normalised standard deviations. It is also seen that the next winner is the original TLBO algorithm having less deviation followed by the scheme of replacement by fresh solutions.

6.2.2 Welded beam design

The results obtained from the single objective optimization of Equation 38 subjected to constraints represented by Equations 39-45 have been solved using the original TLBO and the modifications suggested in the previous chapter. The calculated values are tabulated in Table 30. The tabulated data is also presented graphically for easy analysis in Figure 21.

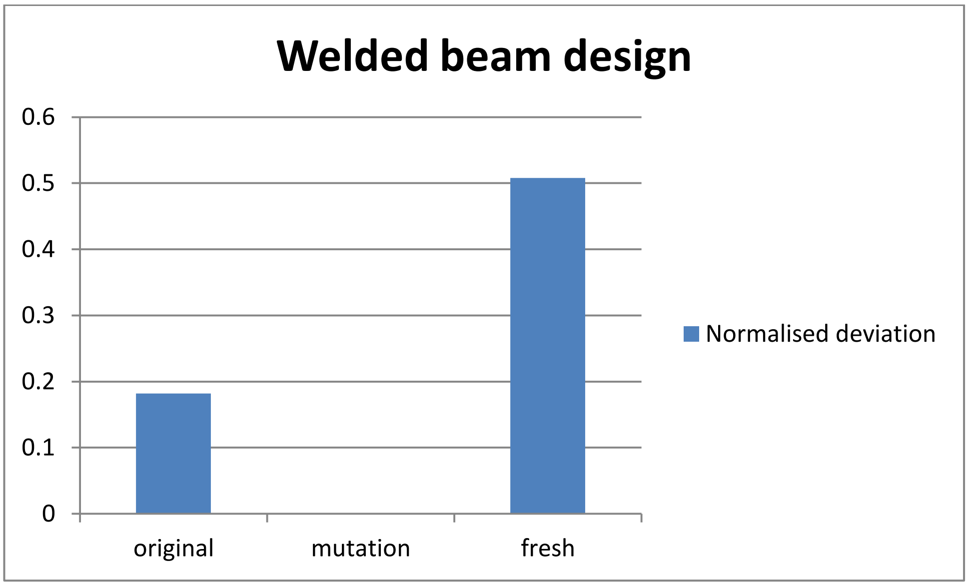

Figure 21 : Comparison graph for welded beam design

On comparative analysis of the table and the graph for the design of welded beam, it is found that the average normalised standard deviations for original TLBO algorithm is 0.182017, Mutation based TLBO is 8.71E-07 and Replacing worst solutions with fresh ones gives 0.508163. This result is quite similar to that of pressure vessel design. Mutation based TLBO has again performed better than its competitors in reaching the global optimal solution in the given number of iterations with zero normalised standard deviations. It is also seen that the next winner is the original TLBO algorithm having less deviation followed by the scheme of replacement by fresh solutions.

6.2.3 Design of tension compression spring

The results obtained from the single objective optimization of Equation 46 subjected to constraints represented by Equations 47-49 have been solved using the original TLBO and the modifications suggested in the previous chapter. The calculated values are tabulated in Table 32. The tabulated data is also presented graphically for easy analysis in Figure 22.

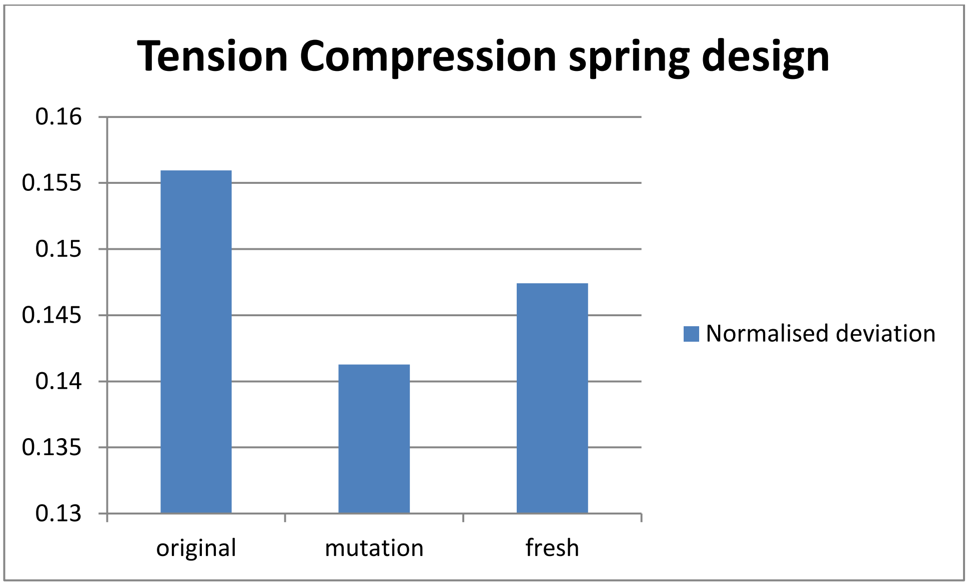

Figure 22 : Comparison graph for tension-compression spring design

On comparative analysis of the table and the graph for the design of tension compression spring, it is found that the average normalised standard deviations for original TLBO algorithm is 0.155941, Mutation based TLBO is 0.141266 and Replacing worst solutions with fresh ones gives 0.147421. It is again evident that Mutation based TLBO has performed better than its competitors in reaching the global optimal solution in the given number of iterations with comparably less normalised standard deviation. However for this problem it is seen that the next winner is the scheme of replacement by fresh solutions having less deviation followed by the original TLBO algorithm. On a close analysis it can also be said that all the three schemes have equally performed and have subtle differences in the overall normalised standard differences.

6.2.4 Parametric optimization of ECM process

The results obtained from the single objective optimization of Equation 30 subjected to constraints represented by Equations 31-33 have been solved using the original TLBO and the modifications suggested in the previous chapter. The calculated values are tabulated in Table 36-38.

Minimization of dimensional inaccuracy

The increase is the dimensional accuracy is achieved by finding the combination of parameters which deliver the minimum value of the expression of dimensional inaccuracy given by Equation 30-a. The calculated values are tabulated in Table 36. The tabulated data is also presented graphically for easy analysis in Figure 23.

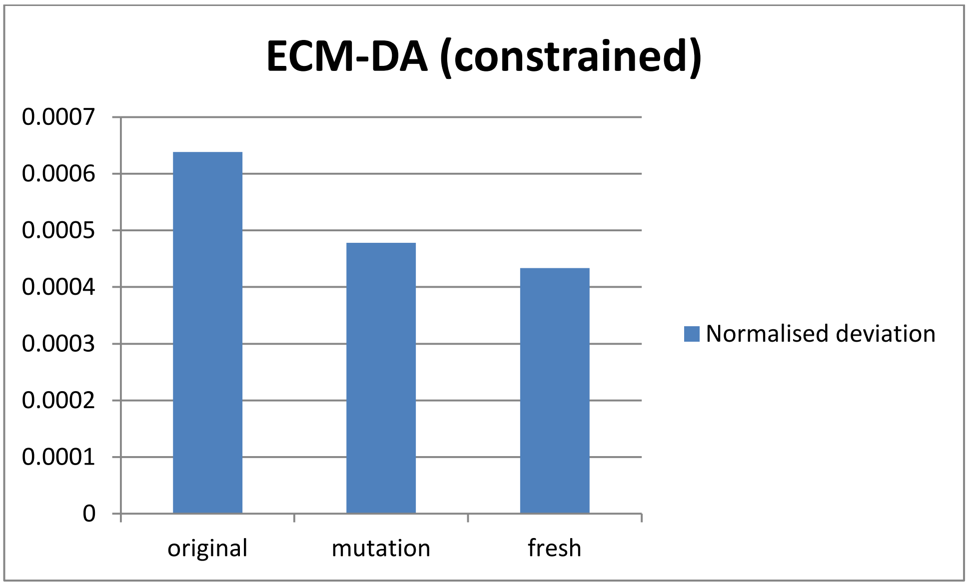

Figure 23 : Comparison graph for ECM-DA-constrained

The single objective optimization of dimensional inaccuracy has yielded a optimal value of 17.4266 µm for the parameter values of tool feed rate *f=8µm/s, electrolyte velocity U=300 cm/s and voltage V=10 V.* Rao et al. [1] attempted this problem by using particle swarm optimization and have given a better value of 15.452 µm for parameter values of tool feed rate *f=8 µm/s, electrolyte velocity U=300 cm/s and voltage V=9.835 V.* However the calculation of passivity constraint using the given parameter values give a negative value of -0.051 and thus leads to violation of this constraint.

On comparative analysis of the table and the graph for the maximization of MRR, it is found that the average normalised standard deviations for original TLBO algorithm is 0.000638, Mutation based TLBO is 0.000478 and Replacing worst solutions with fresh ones gives 0.000434. Contrary to the results found so far Mutation based TLBO has not performed better than its competitors in reaching the global optimal solution in the given number of iterations with zero normalised standard deviations. Instead the scheme of replacement by fresh solutions has given better results for such kind of optimization problem. However the Mutation scheme has performed better than the original TLBO algorithm.

Maximizing tool life

The increase is the tool life is achieved by finding the combination of parameters which deliver the minimum value of the expression of sparks per unit length given by Equation 30-b. The calculated values are tabulated in Table 37. The tabulated data is also presented graphically for easy analysis in Figure 24.

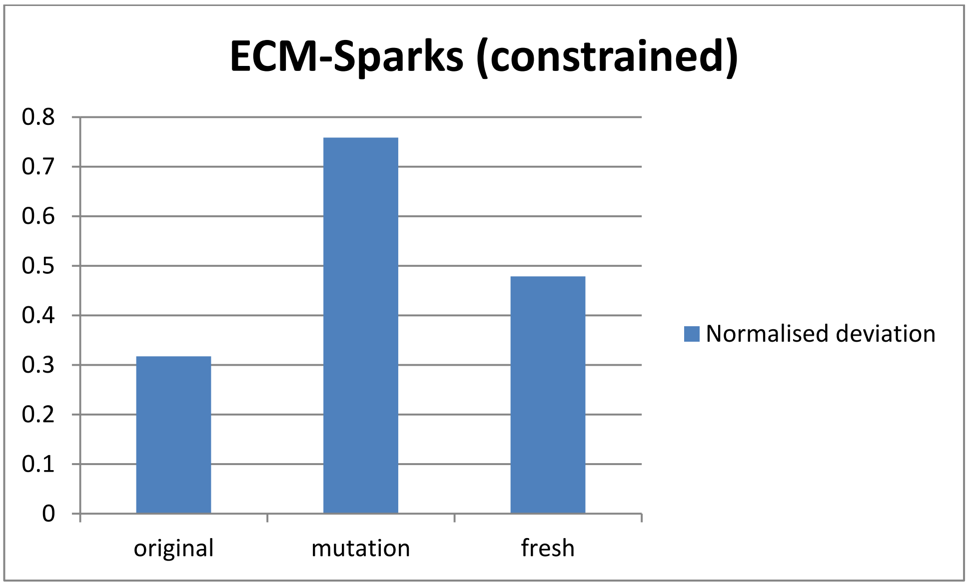

Figure 24 : Comparison graph for ECM-Sparks-constrained

The single objective optimization of Equation 30-b (sparks per unit length) has yielded a optimal value of 1.0541 for the parameter values of tool feed rate *f=8µm/s, electrolyte velocity U=300 cm/s and voltage V=21 V.* This optimal value and the corresponding parametric combination is same as those found by using other evolutionary algorithms by previous researchers.

On comparative analysis of the table and the graph for the minimization of OC, it is found that the average normalised standard deviations for original TLBO algorithm is 0.317677, Mutation based TLBO is 0.758275 and Replacing worst solutions with fresh ones gives 0.478566. It is of a note that in this particular optimization problem has outperformed the modifications proposed in this thesis. However for this problem it is seen that the next winner is the scheme of replacement by fresh solutions having less deviation followed by the mutation based TLBO algorithm.

Maximization of MRR

The material removal rate in this analysis is considered to be the same as the rate of tool feed. The expression for the material removal rate is simple and does not require use of an algorithm. However, given the relevant constraints the optimization was carried out by all the three schemes already discussed.

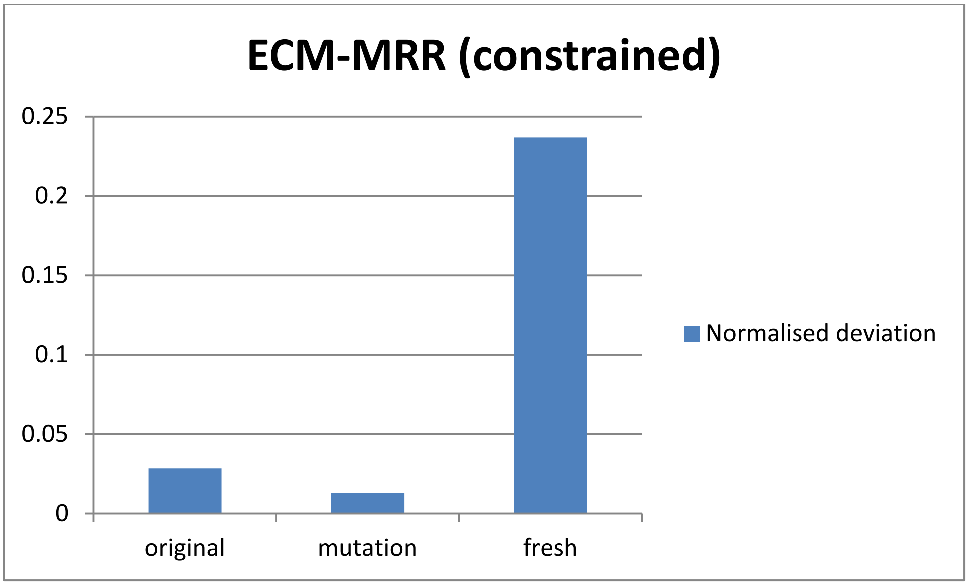

Figure 25 : Comparison graph for ECM-MRR-constrained

The single objective optimization of Equation 30-c (material removal rate) has yielded a optimal value of 26.67 for the parameter values of tool feed rate *f=26.088 µm/s, electrolyte velocity U=300 cm/s and voltage V=21 V.* This optimal value and the corresponding parametric combination is same as those found by using other evolutionary algorithms by previous researchers.

On comparative analysis of the Table 38 and the graph (see Figure 25) for this multi-objective problem, it is found that the average normalised standard deviations for original TLBO algorithm is 0.028538, Mutation based TLBO is 0.012909 and Replacing worst solutions with fresh ones gives 0.236877. In this particular case it is found that Mutation based TLBO has performed better than original TLBO and the scheme of replacement by fresh solutions, in reaching the global optimal solution in the given number of iterations with near-zero normalised standard deviation.

Table 29 : Combined results of all constrained optimization problems

Examples	original	mutation	fresh
Welded beam design	0.182017	8.71E-07	0.508163
Pressure vessel design	0.03341	0.000445	0.205302
Tension Compression spring design	0.155941	0.141266	0.147421
ECM-Material removal rate	0.212543	0.082417	0.064981
ECM-Radial overcut	0.095662	4.89E-06	0.031149
ECM-Multi objective	0.476929	6.79E-05	6.79E-05
ECM-DA-constrained	0.000638	0.000478	0.000434
ECM-Sparks-constrained	0.317677	0.758275	0.478566
ECM-MRR-constrained	0.028538	0.012909	0.236877

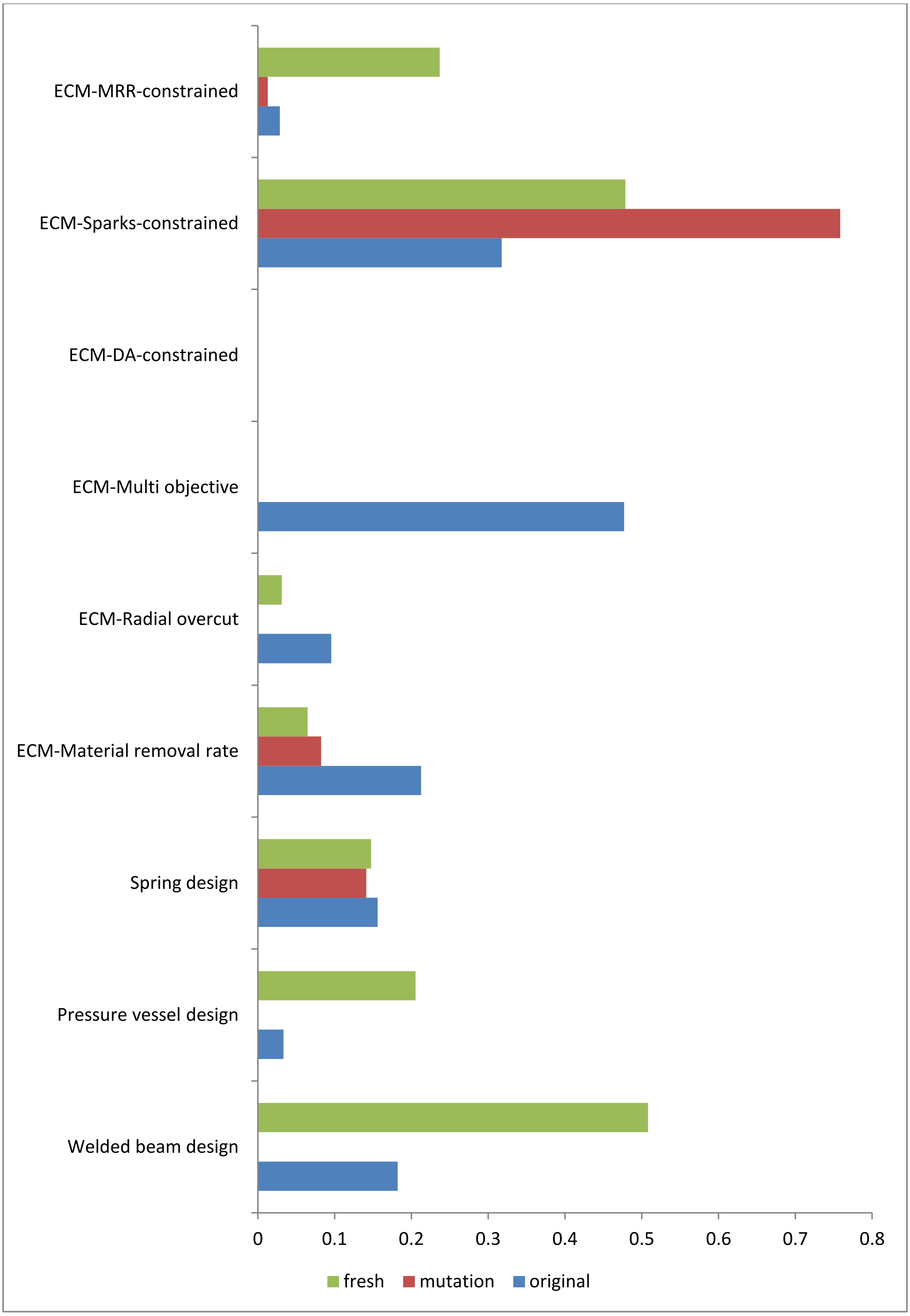

Figure 26 : Results based on all examples

Table 30 : Comparison table for welded beam design

published optimal f(x)=1.724852												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	1.94491158	1.7248534	2.23983308	Deviation from published optimum solution	0.22005958	1.40E-06	0.51498108	Normalized deviation	0.12758172	8.13E-07	0.29856537
2	99	1.76199562	1.72485291	2.21259954		0.03714362	9.13E-07	0.48774754		0.02153438	5.29E-07	0.28277646
3	10	2.06913446	1.72485513	4.24910143		0.34428246	3.13E-06	2.52424943		0.19960116	1.82E-06	1.46345856
4	57	1.83910162	1.72485354	2.25232384		0.11424962	1.54E-06	0.52747184		0.06623734	8.90E-07	0.30580701
5	89	2.24742062	1.72485371	2.2261385		0.52256862	1.71E-06	0.5012865		0.30296433	9.91E-07	0.29062581
6	68	2.48541429	1.7248529	3.29378463		0.76056229	9.00E-07	1.56893263		0.44094351	5.22E-07	0.9096042
7	1	1.81945326	1.72485361	1.94425139		0.09460126	1.61E-06	0.21939939		0.05484602	9.36E-07	0.12719896
8	43	1.77563087	1.7248533	2.74283647		0.05077887	1.30E-06	1.01798447		0.02943955	7.56E-07	0.59018656
9	36	2.10975375	1.72485508	2.89960092		0.38490175	3.08E-06	1.17474892		0.22315059	1.78E-06	0.6810723
10	24	2.2526587	1.72485515	2.78754349		0.5278067	3.15E-06	1.06269149		0.30600115	1.83E-06	0.6161059
11	49	2.3585061	1.72485259	2.22213029		0.6336541	5.92E-07	0.49727829		0.36736723	3.43E-07	0.288302
12	27	2.01646789	1.72485308	2.22964772		0.29161589	1.08E-06	0.50479572		0.1690672	6.26E-07	0.29266031
13	81	2.57217341	1.72485315	3.08045844		0.84732141	1.15E-06	1.35560644		0.49124297	6.66E-07	0.78592624
14	6	1.94506563	1.72485363	3.24708494		0.22021363	1.63E-06	1.52223294		0.12767103	9.45E-07	0.8825296
15	77	1.79303264	1.72485322	2.21222985		0.06818064	1.22E-06	0.48737785		0.0395284	7.08E-07	0.28256213
16	51	2.20241675	1.72485317	2.18133573		0.47756475	1.17E-06	0.45648373		0.27687288	6.76E-07	0.26465095
17	33	1.82041238	1.72485335	2.32964374		0.09556038	1.35E-06	0.60479174		0.05540208	7.85E-07	0.35063399
18	17	1.88259921	1.72485342	3.13495247		0.15774721	1.42E-06	1.41010047		0.0914555	8.22E-07	0.81751969
19	92	1.82579081	1.724853	2.19601932		0.10093881	9.99E-07	0.47116732		0.05852027	5.79E-07	0.27316391
20	62	2.05415028	1.72485269	2.34565991		0.32929828	6.92E-07	0.62080791		0.19091393	4.01E-07	0.35991952
					Avg. dev	0.31395249	1.50E-06	0.87650678		0.18201706	8.708E-07	0.50816347

Table 31 : Comparison table for pressure vessel design

published optimal f(x)=5897.91												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	5901.23719	5907.08946	7456.91243	Deviation from published optimum solution	3.32718602	9.17946358	1559.00243	Normalized deviation	0.00056413	0.00155639	0.26433134
2	99	6257.57814	5898.03708	8365.20079		359.668141	0.12708379	2467.29079		0.0609823	2.1547E-05	0.41833307
3	10	5916.53169	5898.83996	6695.97294		18.6216894	0.92995522	798.062938		0.00315734	0.00015768	0.13531284
4	57	6142.29146	5898.07213	6840.47103		244.381462	0.16212892	942.561031		0.04143526	2.7489E-05	0.15981272
5	89	6110.58093	5897.94255	6672.89231		212.670925	0.032551	774.982307		0.03605869	5.52E-06	0.13139948
6	68	6245.52118	5899.00561	7340.95019		347.611184	1.09561027	1443.04019		0.05893803	0.00018576	0.24466975
7	1	6001.08646	5898.13251	6692.84677		103.176459	0.22250924	794.936766		0.01749373	3.7727E-05	0.13478279
8	43	6172.411	5897.95163	6750.43876		274.501	0.04163384	852.528755		0.04654208	7.06E-06	0.1445476
9	36	6036.33936	5898.72656	7205.92304		138.429364	0.81655843	1308.01304		0.02347092	0.00013845	0.22177569
10	24	6670.25262	5897.94294	6677.6506		772.342619	0.03294217	779.740599		0.13095192	5.59E-06	0.13220626
11	49	5930.94774	5899.46504	6942.62651		33.0377378	1.55504202	1044.71651		0.0056016	0.00026366	0.17713334
12	27	6005.28987	5898.02143	7124.67095		107.379866	0.11142645	1226.76095		0.01820643	1.8893E-05	0.20799927
13	81	6076.66962	5897.91179	7343.87584		178.759623	0.00179036	1445.96584		0.03030898	3.04E-07	0.2451658
14	6	6010.95436	5898.09144	7191.59521		113.04436	0.18144038	1293.68521		0.01916685	3.0764E-05	0.21934638
15	77	6166.28204	5901.77945	7337.45644		268.372037	3.86945175	1439.54644		0.0455029	0.00065607	0.24407738
16	51	6068.21953	5905.04211	6589.82682		170.309532	7.13211204	691.916816		0.02887625	0.00120926	0.11731559
17	33	6023.82464	5921.80291	6631.97103		125.914645	23.892914	734.061025		0.02134903	0.00405108	0.12446121
18	17	6060.48492	5900.94679	7621.2581		162.57492	3.03679042	1723.3481		0.02756484	0.00051489	0.2921964
19	92	5998.29862	5897.88898	7016.42514		100.388624	0.02101628	1118.51514		0.01702105	3.56E-06	0.18964602
20	62	6104.39159	5897.90841	7676.2472		206.48159	0.00159483	1778.3372		0.03500928	2.70E-07	0.30151989
					Avg. dev	197.049648	2.62220075	1210.8506		0.03341008	0.0004446	0.20530164

Table 32 : Comparison table for tension-compression spring design

published optimal f(x)=0.012665												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	0.01756211	0.01438042	0.01490151	Deviation from published optimum solution	0.00489711	0.00171542	0.00223651	Normalized deviation	0.38666512	0.1354458	0.17658956
2	99	0.01297131	0.01443693	0.02170423		0.00030631	0.00177193	0.00903923		0.02418566	0.13990744	0.71371737
3	10	0.01298665	0.0145497	0.01508633		0.00032165	0.0018847	0.00242133		0.02539709	0.14881172	0.19118278
4	57	0.01495708	0.01417781	0.01342311		0.00229208	0.00151281	0.00075811		0.18097738	0.11944841	0.05985834
5	89	0.01430651	0.01480888	0.01296528		0.00164151	0.00214388	0.00030028		0.12961019	0.16927578	0.02370957
6	68	0.01325289	0.01322389	0.0133504		0.00058789	0.00055889	0.0006854		0.04641858	0.0441289	0.05411785
7	1	0.01304471	0.01631201	0.02413228		0.00037971	0.00364701	0.01146728		0.02998088	0.2879597	0.90543036
8	43	0.01515694	0.01338569	0.01335891		0.00249194	0.00072069	0.00069391		0.19675789	0.05690391	0.05478987
9	36	0.01288005	0.01446399	0.0128771		0.00021505	0.00179899	0.0002121		0.01697983	0.14204448	0.01674694
10	24	0.01471251	0.0132374	0.0127245		0.00204751	0.0005724	5.95E-05		0.16166663	0.04519559	0.00469801
11	49	0.01289382	0.0138155	0.01314649		0.00022882	0.0011505	0.00048149		0.01806675	0.09084122	0.03801768
12	27	0.01356315	0.01340014	0.01337975		0.00089815	0.00073514	0.00071475		0.07091623	0.05804515	0.05643526
13	81	0.01797314	0.01521061	0.01358551		0.00530814	0.00254561	0.00092051		0.41911895	0.20099604	0.07268166
14	6	0.01773663	0.01360432	0.01334119		0.00507163	0.00093932	0.00067619		0.40044437	0.07416675	0.05339028
15	77	0.0149984	0.01576479	0.01280169		0.0023334	0.00309979	0.00013669		0.18424015	0.24475274	0.01079299
16	51	0.01536332	0.01400133	0.01345845		0.00269832	0.00133633	0.00079345		0.21305325	0.10551367	0.06264914
17	33	0.01590429	0.01432192	0.01307477		0.00323929	0.00165692	0.00040977		0.25576721	0.13082696	0.03235437
18	17	0.01547969	0.01631201	0.01293923		0.00281469	0.00364701	0.00027423		0.22224123	0.2879597	0.0216526
19	92	0.01321494	0.01548839	0.01306064		0.00054994	0.00282339	0.00039564		0.04342241	0.22292879	0.03123847
20	62	0.0138418	0.01418693	0.01733041		0.0011768	0.00152193	0.00466541		0.09291735	0.12016853	0.36837055
					Avg. dev	0.001975	0.00178913	0.00186709		0.15594136	0.14126606	0.14742118

Table 33 : Comparison table for ECM-Material removal rate

published optimal f(x)=1.4551												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	1.091252	1.455104	1.0912525	Deviation from published optimum solution	0.3638475	4.40E-06	0.3638475	Normalized deviation	0.25004982	3.02E-06	0.25004982
2	99	1.091252	1.455104	1.4551044		0.3638475	4.40E-06	4.40E-06		0.25004982	3.02E-06	3.02E-06
3	10	1.091252	1.455104	1.4551044		0.3638475	4.40E-06	4.40E-06		0.25004982	3.02E-06	3.02E-06
4	57	1.455104	1.383316	1.4551044		4.40E-06	0.0717844	4.40E-06		3.02E-06	0.04933297	3.02E-06
5	89	1.091252	1.383316	1.0912525		0.3638475	0.0717844	0.3638475		0.25004982	0.04933297	0.25004982
6	68	1.091252	1.455104	1.4551044		0.3638475	4.40E-06	4.40E-06		0.25004982	3.02E-06	3.02E-06
7	1	1.091252	1.091252	1.4551044		0.3638475	0.3638475	4.40E-06		0.25004982	0.25004982	3.02E-06
8	43	1.091253	1.455104	1.4551044		0.3638475	4.40E-06	4.40E-06		0.25004982	3.02E-06	3.02E-06
9	36	1.455104	1.455104	1.4551044		4.40E-06	4.40E-06	4.40E-06		3.02E-06	3.02E-06	3.02E-06
10	24	1.455104	1.091253	1.4551044		4.40E-06	0.3638475	4.40E-06		3.02E-06	0.25004982	3.02E-06
11	49	1.091253	1.383316	1.4551044		0.3638475	0.0717844	4.40E-06		0.25004982	0.04933297	3.02E-06
12	27	1.091252	1.091252	1.4551044		0.3638475	0.3638475	4.40E-06		0.25004982	0.25004982	3.02E-06
13	81	1.091252	1.091252	1.0912525		0.3638475	0.3638475	0.3638475		0.25004982	0.25004982	0.25004982
14	6	1.091252	1.091252	1.4551044		0.3638475	0.3638475	4.40E-06		0.25004982	0.25004982	3.02E-06
15	77	1.091253	1.091252	1.3833156		0.3638475	0.3638475	0.0717844		0.25004982	0.25004982	0.04933297
16	51	1.091252	1.455104	1.4551044		0.3638475	4.40E-06	4.40E-06		0.25004982	3.02E-06	3.02E-06
17	33	1.091253	1.455104	1.4551044		0.3638475	4.40E-06	4.40E-06		0.25004982	3.02E-06	3.02E-06
18	17	1.091253	1.455104	1.0912525		0.3638475	4.40E-06	0.3638475		0.25004982	3.02E-06	0.25004982
19	92	1.091253	1.455104	1.0912525		0.3638475	4.40E-06	0.3638475		0.25004982	3.02E-06	0.25004983
20	62	1.091252	1.455104	1.4551044		0.3638475	4.40E-06	4.40E-06		0.25004982	3.02E-06	3.02E-06
					Avg. dev	0.30927104	0.1199243	0.09455418		0.2125428	0.08241656	0.06498122

Table 34 : Comparison table for ECM-Radial overcut

published optimal f(x)=0.08185												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	0.0818496	0.08185	0.08185	Deviation from published optimum solution	4.00E-07	4.00E-07	4.00E-07	Normalized deviation	4.89E-06	4.89E-06	4.89E-06
2	99	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
3	10	0.0818496	0.08185	0.132834		4.00E-07	4.00E-07	0.0509836		4.89E-06	4.89E-06	0.62289065
4	57	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
5	89	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
6	68	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
7	1	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
8	43	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
9	36	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
10	24	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
11	49	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
12	27	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
13	81	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
14	6	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
15	77	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
16	51	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
17	33	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
18	17	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
19	92	0.0818496	0.08185	0.08185		4.00E-07	4.00E-07	4.00E-07		4.89E-06	4.89E-06	4.89E-06
20	62	0.23844158	0.08185	0.08185		0.15659158	4.00E-07	4.00E-07		1.91315306	4.89E-06	4.89E-06
					Avg. dev	0.00782996	4.00E-07	0.0025496		0.0956623	4.89E-06	0.03114918

Table 35 : Comparison table for ECM-Multi objective

published optimal f(x)=0.3488												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	0.34882369	0.34882369	0.34882369	Deviation from published optimum solution	2.3693E-05	2.3693E-05	2.3693E-05	Normalized deviation	6.7926E-05	6.7926E-05	6.7926E-05
2	99	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
3	10	1.18047023	0.34882369	0.34882369		0.83167023	2.3693E-05	2.3693E-05		2.38437566	6.7926E-05	6.7926E-05
4	57	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
5	89	1.18047023	0.34882369	0.34882369		0.83167023	2.3693E-05	2.3693E-05		2.38437566	6.7926E-05	6.7926E-05
6	68	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
7	1	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
8	43	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
9	36	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
10	24	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
11	49	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
12	27	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
13	81	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
14	6	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
15	77	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
16	51	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
17	33	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
18	17	0.34882369	0.34882369	0.34882369		2.3693E-05	2.3693E-05	2.3693E-05		6.7926E-05	6.7926E-05	6.7926E-05
19	92	1.18047023	0.34882369	0.34882369		0.83167023	2.3693E-05	2.3693E-05		2.38437566	6.7926E-05	6.7926E-05
20	62	1.18047023	0.34882369	0.34882369		0.83167023	2.3693E-05	2.3693E-05		2.38437566	6.7926E-05	6.7926E-05
					Avg. dev	0.166353	2.3693E-05	2.3693E-05		0.47692947	6.7926E-05	6.7926E-05

Table 36 : Comparison table for ECM-dimensional accuracy-constrained

published optimal f(x)=0.3488												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	17.43138	17.42973	17.43794	Deviation from published optimum solution	0.004778	0.003126	0.011342	Normalized deviation	0.000274	0.000179	0.000651
2	99	17.43417	17.43253	17.45044		0.007567	0.005927	0.023844		0.000434	0.00034	0.001368
3	10	17.4293	17.44628	17.42682		0.002705	0.019685	0.000217		0.000155	0.00113	1.25E-05
4	57	17.43943	17.43033	17.43063		0.012831	0.003728	0.004025		0.000736	0.000214	0.000231
5	89	17.42652	17.42884	17.42641		8.36E-05	0.002239	0.000191		4.8E-06	0.000128	1.1E-05
6	68	17.44454	17.43697	17.42632		0.017944	0.01037	0.000275		0.00103	0.000595	1.58E-05
7	1	17.44312	17.42643	17.42735		0.016521	0.000173	0.000746		0.000948	9.95E-06	4.28E-05
8	43	17.42992	17.42871	17.44498		0.003323	0.002107	0.018377		0.000191	0.000121	0.001055
9	36	17.4401	17.43351	17.42658		0.013499	0.006909	2.32E-05		0.000775	0.000396	1.33E-06
10	24	17.45012	17.42632	17.42632		0.023521	0.000281	0.00028		0.00135	1.61E-05	1.61E-05
11	49	17.42632	17.45188	17.44574		0.000281	0.025283	0.019136		1.62E-05	0.001451	0.001098
12	27	17.43321	17.4399	17.43365		0.006613	0.013296	0.007047		0.000379	0.000763	0.000404
13	81	17.44542	17.42866	17.43378		0.01882	0.002062	0.007181		0.00108	0.000118	0.000412
14	6	17.44989	17.4437	17.44654		0.023288	0.017097	0.019943		0.001336	0.000981	0.001144
15	77	17.44857	17.43579	17.45691		0.021973	0.009192	0.030309		0.001261	0.000527	0.001739
16	51	17.42634	17.42643	17.42645		0.000262	0.000173	0.000152		1.5E-05	9.91E-06	8.71E-06
17	33	17.43669	17.42639	17.42632		0.010086	0.000212	0.000279		0.000579	1.22E-05	1.6E-05
18	17	17.44313	17.42835	17.42634		0.016531	0.001746	0.000257		0.000949	0.0001	1.48E-05
19	92	17.44358	17.44421	17.43352		0.016983	0.017607	0.006924		0.000975	0.00101	0.000397
20	62	17.43149	17.45207	17.42718		0.00489	0.025472	0.000584		0.000281	0.001462	3.35E-05
					Avg. dev	0.011125	0.008334	0.007557		0.000638	0.000478	0.000434

Table 37 : Comparison table for ECM-sparks-constrained

published optimal f(x)=0.3488												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	1.054108	1.054108	1.054108	Deviation from published optimum solution	4.07E-07	4.07E-07	4.07E-07	Normalized deviation	3.86E-07	3.86E-07	3.86E-07
2	99	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
3	10	1.47143	1.054291	1.054108		0.417322	0.000183	4.07E-07		0.395901	0.000173	3.86E-07
4	57	1.054108	1.054108	1.892458		4.07E-07	4.07E-07	0.83835		3.86E-07	3.86E-07	0.795317
5	89	1.054108	1.054108	9.482121		4.07E-07	4.07E-07	8.428013		3.86E-07	3.86E-07	7.995398
6	68	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
7	1	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
8	43	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
9	36	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
10	24	5.748607	13.41595	1.815898		4.694499	12.36184	0.76179		4.453528	11.7273	0.722687
11	49	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
12	27	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
13	81	1.054108	4.678154	1.054108		4.07E-07	3.624046	4.07E-07		3.86E-07	3.438021	3.86E-07
14	6	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
15	77	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
16	51	2.639602	1.054108	1.115149		1.585494	4.07E-07	0.061041		1.50411	3.86E-07	0.057908
17	33	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
18	17	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
19	92	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
20	62	1.054108	1.054108	1.054108		4.07E-07	4.07E-07	4.07E-07		3.86E-07	3.86E-07	3.86E-07
					Avg. dev	0.334866	0.799304	0.50446		0.317677	0.758275	0.478566

Table 38 : Comparison table for ECM-MRR-constrained

published optimal f(x)=0.3488												
Sl. No.	seed	original	mutation	fresh		original	mutation	fresh		original	mutation	fresh
1	74	26.66985	26.11387	26.07686	Deviation from published optimum solution	0.00015	0.556128	0.593141	Normalized deviation	5.63E-06	0.020852	0.02224
2	99	26.53651	26.11614	25.88367		0.13349	0.553865	0.786333		0.005005	0.020767	0.029484
3	10	26.11477	26.11614	19.61423		0.555229	0.553859	7.055771		0.020818	0.020767	0.264558
4	57	26.09478	26.11614	26.10915		0.575224	0.553864	0.560852		0.021568	0.020767	0.021029
5	89	26.66916	26.6556	26.08551		0.000841	0.014404	0.58449		3.15E-05	0.00054	0.021916
6	68	26.66796	26.11562	26.02038		0.00204	0.554383	0.64962		7.65E-05	0.020787	0.024358
7	1	26.66862	26.66628	26.0288		0.001377	0.003721	0.641197		5.16E-05	0.00014	0.024042
8	43	26.66991	26.65193	12.9647		9.23E-05	0.018071	13.7053		3.46E-06	0.000678	0.513884
9	36	26.66767	26.11488	23.47437		0.00233	0.555116	3.195631		8.74E-05	0.020814	0.119821
10	24	19.94934	26.11411	8		6.720663	0.555893	18.67		0.251993	0.020843	0.700037
11	49	26.6678	26.34735	26.11141		0.002198	0.322649	0.558588		8.24E-05	0.012098	0.020944
12	27	26.13363	26.11389	26.11036		0.53637	0.556109	0.559637		0.020111	0.020851	0.020984
13	81	26.66816	26.66651	26.09325		0.001837	0.003488	0.576751		6.89E-05	0.000131	0.021625
14	6	26.66771	26.11392	8		0.002286	0.556083	18.67		8.57E-05	0.02085	0.700037
15	77	26.67038	26.28077	15.67654		0.000381	0.389233	10.99346		1.43E-05	0.014594	0.412203
16	51	19.9934	26.11435	12.14871		6.676601	0.555647	14.52129		0.250341	0.020834	0.54448
17	33	26.66801	26.66745	26.09099		0.001994	0.002554	0.579008		7.48E-05	9.58E-05	0.02171
18	17	26.66862	26.66663	26.11177		0.001382	0.003372	0.558231		5.18E-05	0.000126	0.020931
19	92	26.6626	26.64895	12.44899		0.007404	0.021049	14.22101		0.000278	0.000789	0.533221
20	62	26.66995	26.11357	8		5.44E-05	0.556426	18.67		2.04E-06	0.020863	0.700037
					Avg. dev	0.761097	0.344296	6.317515		0.028538	0.012909	0.236877

Chapter 7: Conclusions

Mechanical elements are integral features of any equipment and structures. The competitive world today demands effective and efficient equipment and machinery which necessitates optimization to be carried out at every stage from conceptualization to manufacturing to reduce the cost and proper utilization of scarce resources. Although non-traditional optimization techniques have been used in the past to solve optimization problems in both design and manufacturing domain but these algorithms have their own limitations and drawbacks. Evolutionary algorithms can effectively address some of the limitations of traditional algorithms; hence widely applied in various fields of engineering with varying degree of success. The quality of solutions generated by these algorithms is highly dependent on the tuning of algorithmic parameters. All evolutionary algorithms such as GA, SA, ABC and others require algorithm specific parameters in addition to the common parameters of population size and number of generations. A change in these algorithmic parameters changes the overall effectiveness of the algorithm. To avoid this difficulty, a population based optimization algorithm and its improved versions are presented in this dissertation and have been applied to different optimization problems of design and manufacturing domain.

The non-conventional machining is a complex process involving large number of parameters which makes the total machining process unpredictable and sensitive to the controlling parameters. Hence, it is imperative to know the correct optimal settings of the controlling parameters for a cost effective machining. In this thesis, three such processes have been considered in which the process control has been difficult due to a large number of parameters acting on each of the processes. The parametric optimization of electro-discharge machining, electro-chemical machining and electro-chemical discharge machining were solved in this thesis using a new evolutionary algorithm TLBO. Both single and multi-objective optimization of the process responses have been carried out for all the machining processes and comparison of results have been performed with other evolutionary algorithms in terms of function evaluations, number of algorithm specific parameters, and better optimal values. TLBO has outperformed its competitors in some or the other aspect as already presented and discussed in the preceding chapter.

It was found that similar to some other evolutionary techniques, TLBO also had the tendency of loosing diversity after some iterations and thus an additional step was required in the algorithm to create population diversity. Incorporation of artificial diversification in the population of solutions already used by other nature inspired algorithms can enhance the probability of escaping the local extremes. *Artificial Immune System* optimization technique uses *Receptor Editing* to provide an addition mean for creating diversification in the population. *Bacteria Foraging* optimization algorithm uses *Elimination and Dispersal* as its third step in the algorithm to reject/modify the worst solution in the population. In this thesis, a similar attempt was made and two modifications have been suggested.

Further improvement in the existing TLBO algorithm has been incorporated using two schemes namely bit string mutation and replacement of worst solutions with fresh ones. Performance evaluation of these modifications have been presented in this dissertation by solving six optimization problems using original TLBO and proposed modifications. It has been found that better results are achieved in reaching the global optimal values by the use of these modifications. However, the results prefer the use of bit string mutation over scheme of replacing the worst solutions with fresh solutions in addition to the original logic of TLBO.

The reason behind the success of proposed modifications lies in its ability to re-route the direction of search away from the region of worst solutions and towards the global ones. Such attempts not only reduces the futile computation efforts near the forbidden search space but also helps the algorithm in case it gets stuck at the local minima or maxima. This concept is similar to the concept of elitism but acts in an opposite way where the rejection of worst solution is done instead of saving the elite solutions.

The proposed modifications have to be further extended to other engineering problems to check for the suitability and robustness. A large amount of research work is required to properly establish the results obtained by this thesis which could not be done due to time constraints.

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Chapter 9: Annexure

This section presents a manual for using the developed code in Matlab 7.0. All the files used by Matlab to successfully run the optimization code are briefly described and instructions are provided lest any modifications are required in the existing code.

This section will be useful to those wishing to fathom or use the logical coding of the optimizing software. It is to be noted that though this code can be further developed to solve very large scale problems, but presently this code is limited to solve only 2 to 4 variables problems involving any number of constraints. Following is the list of all the function and script files used by Matlab. The user intending to use the program should ensure availability of all these files in the current folder of the Matlab.

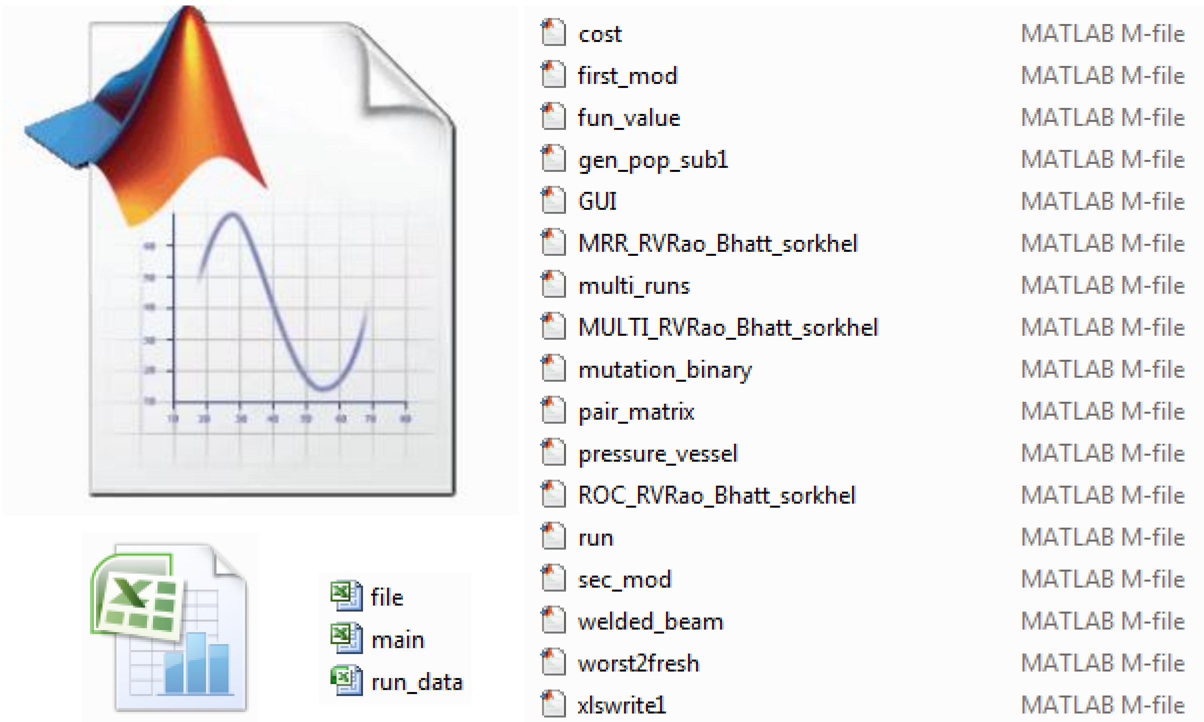

Figure 27 : Snapshot of files used by Matlab

Along with the Matlab files excel files are also required at some instances in the program, however the user can use other excel files with different names, provided he knows the syntax of *xlswrite( )* and *xlswrite( )* functions. These functions are inbuilt in the Matlab and account for import and export of data to excel files. All the necessary files have been briefly discussed below, and the user is expected to be thorough with them before attempting the use of the optimization code. Any changes to the existing code elsewhere may be erroneous unless the user is suitably conversed with Matlab programming.

Filename :cost.m

This is a function file in Matlab where the input is the array of all the subjects and the number of learners associated with it. The function output is the cost array for all the learners. The term *cost* is used at many instances and in many forms, and it is to be noted that it analogous to the value of objective function defined for the current optimization problem.

```
function [ cost_all ] = cost( sub1,sub2,sub3,sub4,no_learners )
```

In the Figure above *sub1, sub2, sub3, sub4* are the array of subjects and *no_learners* is the number of learners for the current problems.

Filename :first_mod.m

This is a function file in Matlab which holds the logic of the Teaching Learning based optimization algorithm. The initial population along with the cost array is fed to this function to receive the final population and its cost array. A single execution of this function incorporates both the Teachers phase and Learners phase to the input population and serves as a single generation for the TLBO algorithm.

```
54 -  TF=1;
55    % Teaching Factor considered as 1
```

Constant teaching factor has been used during the complete execution of the algorithm. The value of teaching factor (*TF*) can be altered for the algorithm here at line # 54. The value of TF generally lies between 1 and 2. No other controlling parameter exists in this file, and thus no alteration should be done in the remaining codes, for the successful execution of this file.

Filename :fun_value.m

This is a function file in Matlab which holds the objective function or cost function.

```
cost=(sub1^2+sub2-11)^2+(sub1+sub2^2-7)^2;
```

The design variables are named as *sub1, sub2, sub 3* and so on. The function inputs the values of design variables and calculates the cost or the objective function value for the presented combination of design variables.

Filename : gen_pop_sub1.m

This function file creates initial population for all the subjects and returns an array. The input parameters are low limit, high limit and the number of learners. A population is created based on the Gaussian Distribution. Certainly this function file is used a number of times in the program execution basad on the number of subjects or design variables.

```
randn('seed',seed);
sub=randn(no_learners,1);
st_dev=(high_lim-low_lim)/6;  %
mean=(high_lim+low_lim)/2;
i=1;
while(i<=no_learners)
    sub(i)=mean+(sub(i)*st_dev);
    i=i+1;
end
```

Above is the snapshot of the code used to generate the population. It is to be noted that an array of normalised random number is used to create a population between 0 and 1, and this population is further used to create initial popouation between the low and high limits.

Filename :multi_runs.m

This is a script file which reads user data from an excel sheet *run_data.xlsx* and based on the user data runs the master script file run.m for multiple times and returns back the program data to another excel file *results.xlsx*. The use of this script is to automate the generation of data for comparison between the different schemes of optimization algorithm.

```
run;
xlswrite1('file',min_cost,'gen',gen);
warning off MATLAB:xlswrite:AddSheet;
```

It should be noted that for exporting data into an excel sheet a special function *xlswrite1*(~)is used. This function is a modified version of *xlswrite*(~) which is found inbuilt in the Matlab library.

Filename :mutation_binary.m

This function is used to augment the proposed modification of bit string mutation with the existing TLBO algorithm. This function inputs the final population generated at the end of each iteration and outputs the modified population array.

```
7 -   Pm=0.2;  %mutation probability
8 -   [~,i]=sort(cost,'descend');
```

It is possible to alter the mutation probability in this function. It can be seen that in Line 7 a mutation probability of 0.2 is assigned to the variable *Pm*. The user is strictly advised to use a low mutation probability value in the code for good results.

Filename :run.m

This is the master script file which controls all the inputs and outputs of the program. The optimization algorithm commences with the execution of this file. The user is advised to clear all existing variables before the execution of this script file.

```
16 -    write2excel=false;%%%%%put false/true to switch off/on
17 -    write2graph=false;%%%%%put false/true to switch off/on
```

As seen in the above snapshot lines 16 and 17 controls the output options which are in addition to the results generated in the Matlab command window.

If the Boolean variable write2excel is assigned a value *true*, the program exports all the data to an excel file named *main.xls*. All the data generated during the Teacher and the Learner phase are written in this excel file for every generation completed. Each generation is properly numbered and uses a different sheet. The exportation of data can be seen online in the excel window as the program advances though all its generations. The writing of huge amounts of data in excel file requires CPU usage and hence the execution speed of the algorithm is affected.

If the Boolean variable write2graph is assigned a value *true*, the program start plotting an online graph where the minimum value, maximum value and the average value of the cost array at the end of every generation is plotted. This online graphical output also slows down the execution of the program.

Regeneration of the results is required for a comparative analysis and as random numbers are employed in the algorithm, a seed value is used to recreate the set of random numbers.

```
50 -    f_evaluations=0;
51 -    seed=xxx(1);
```

In line # 51 it can be seen that a variable *xxx*(1) is assigned as seed value. This *xxx* variable value is currently imported from the excel file *run_data.xlsx*

The snapshot below declares the input of low and high limits for each subject or design variable and the number of learners in the population.

```
%-------------------------PARAMETERS---
no_learners=100;
sub1_high=0.1;sub1_low=99;
sub2_high=0.1;sub2_low=99;
sub3_high=10;sub3_low=200;
sub4_high=10;sub4_low=200;
%-------------------------------------
```

In the line # 53 variable *no_learners* is assigned a numerical value which decides the number of learners in the optimization problem considered. It is imperative to know that the program code is limited to the use of only even numbers for this variable. In line numbers 54 to 57 low limit and high limits are entered for each subject respectively.

The '*for*' loop starting at line # 68 as shown below decides on the maximum number of generations for the algorithm. In the napshot below it can be seen that presently the maximum number of generations is kept at 1000.

```
68 -  for t=1:1000% no of generation from 1: 200
```

The value can assume only positive integer values and can be directly changed in the code before the execution of the script file.

Lines 87 to 90 are currently formatted as a comment as shown in the snapshot below. These lines can be uncommented and used if a comparative analysis is to be performed based on already published results.

```
87    % if min_cost>opt_low && min_cost<opt_high
88    %     fprintf('total number  of generations = %g\n',t);
89    %     break;
90    % end
```

The above set of codes halts the optimization algorithm as soon as an already published optimal value is generated within the final population at the end of generation. During such halt of the algorithm the results displays the total number of generation in which the optimal value was achieved by the optimizing algorithm.

Filename : worst2fresh.m

This function is used to implement the proposed modification where the worst solution in the population is replaced by fresh solutions. This function inputs the final population generated at the end of each iteration and outputs the modified population array.

```
7 -   Pm=0.2;  %selection probability
8 -   [~,i]=sort(cost,'descend');
```

It is possible to alter the selection probability in this function. It can be seen that in Line 7 a selection probability of 0.2 is assigned to the variable *Pm*. The user is strictly advised to use a low selection probability value in the code for good results.

Filename : xlswrite1.m

This is a modified version of xlswrite(~) function which is found inbuilt in Matlab library. This function opens and closes the excel file for each instance of data export. The algorithm used for the optimization has numerous instances where data is to be written in excel files. In using this modified function, the excel file is opened at the start of the program run and is closed only after successful completion of all the generations. This modification is necessary to speed up the writing process in excel files.