Chapter 1

Introduction

This chapter starts with an introduction to Electron Beam Welding (EBW) process and its applications in various fields. A review of the available literature regarding EBW shows the type and extent of work done earlier, and the unexplored areas left thereafter. The chapter then focuses on the application and utility of soft computing in modeling of EBW process. After highlighting the aims and objectives of the present research work, the scholar claims the contributions made by him in this study. The final section of this chapter lays down the layout of the thesis.

1.1 Introduction to Electron Beam Welding

Electron beam welding is a fusion welding process. Here, the heat required to fuse metal is obtained, when a concentrated beam of high velocity electrons strikes the surfaces to be joined. The kinetic energy of the electrons changes to thermal energy, and thereby, the pieces to be joined melt and finally join upon solidification.

Electron beams can produce high quality welds, free from defects like porosity and contamination at very high speeds. The fusion zone and heat affected zone are extremely narrow. The weld distortion problem, compared to other welding processes, is considerably less, as the input energy is concentrated in a very narrow zone. Highly reactive materials like titanium, zirconium, etc. may be welded, without any contamination by this process, as the welding is performed at a very high degree of vacuum. Weld materials as thin as 0.025 mm to as thick as 100 mm steel can be easily welded in a single pass by this process.

The electron beam is usually generated from a triode system that comprises of a heated filament (cathode), a bias cup and an anode. The electrons, after being generated, are subjected to a huge potential difference called accelerating potential [1]. The accelerated electrons are then focused by an electrostatic lens. The beam can also be made to oscillate in a circular motion by means of an alternating current whose frequency may be varied up to 20,000 Hz. Electron beam welding is influenced by a large number of parameters. This include material to be welded, type of EBW device and different working parameters. The subsequent paragraphs discuss the history of EBW, EBW-related equipments and information related to the welding of ferrous, non-ferrous and dissimilar metals using electron beams.

1.1.1 A Brief History of Electron Beam Welding

Electron was discovered by J.J. Thompson in the year as early as 1897. Fifty years later, in the year 1948, K.H.Steigerwald noticed that a huge heat was generated, when high speed electrons impinged on a metallic target. During his work at the Suddeutsche Laboratory, he realized that high intensity electron beams, generated during experiments with electron microscopy, could melt the anodes. Almost ten years later, during November 1957, Dr. J. A. Stohr of the French Atomic Commission made public the first electron beam welding unit made at Scaleys laboratories. It could weld Zircoloy reactor components very well. After 1960, more radical advances took place as non-vacuum welding technique was first achieved by Heraeus. By the mid of 60s, a closed-circuit TV could also be used for viewing the welding process.

It is also said that by mid 1950s [2], completely independent and unrelated to the above activities, Wyman of the Hanford Atomic Products Operation of the General Electric Company initiated work in this field too. Amongst others who contributed to the development of electron beam welding were Briola, Adams and Olshansky. Olshansky's work in 1958 appeared to be the earliest Soviet reference.

During early 1960s, the field of work of electron beam welding in France was mostly in the area of welding of fuel elements for atomic industry, whereas in the United States, during the same period, the research was carried out to weld heavy gauges of aluminum, stainless steels and refractory metals [3]. In 1963 [4], an electron beam welding gun was developed, which could weld in atmospheric conditions. The quality of weld, in atmospheric electron beam welding, was at par with those welded in vacuum. The vacuum electron beam welding process had the greatest limitations regarding working chamber size for welding of large sized components. The other limitation was the working distance below the gun. Welding of ship hulls, missile cases, pressure tanks, hydraulic tubing and cable sheathing were few immediate potential applications of the newly developed process. In July of 1966, a new breed of electron beam welding equipment called CV2 was developed by Sciaky Electric Welding Machines ltd. [5] having two chambers. One was the Gun Chamber and the other was the Work Chamber. The gun chamber was maintained at a lower pressure than the work chamber. Such soft vacuum machines are being built till date. Another way of tackling larger component was a concept of mobile EBW gun [6]. A mobile gun was developed at Clover, in France, in 1973. Hamilton Standard division [7] of the United Aircraft Corporation constructed an electron beam welding machine, which automated the pipeline joining process. EBW was not only utilized in the industries but also effectively used in space exploration. A battery powered 2 kW electron beam welder developed by Westinghouse Electric Company [8] could be used for repairing job in space.

By 1974, digital computers were used in designing electron beam machines. This gave an insight into the detailed working of a gun rather than the hit-and-miss methods of designing. A computer aided designed 75 kW machine [9] could weld 200 mm thick steel and over 300 mm thick aluminum plates.

1.1.2 Electron Beam Welding and Soft Computing

In order to successfully weld with electron beam there are many parameters (machine and material) which need to be properly controlled. A few of them are:

- level of vacuum in the gun and work chambers,
- current required to heat the emitter to eject sufficient quantity of electrons,
- accelerating voltage between the emitter and the hollow anode, which accelerates the electrons towards the target,
- current in the focusing coil required to focus the electrons on to the target,
- stand-off distance between the gun and the target,
- type of material to be welded,
- thickness of the materials,
- speed of welding.

Thus, it can be seen that a welder has to have enough expertise in order to successfully weld. To select proper inputs of the above mentioned parameters either the welder has to have a good intuition or a past experience of welding on that material. One step ahead, the welder also may be interested to know different mechanical and metallurgical properties of the welded material. Thus, there always exists, a relationship between the inputs to a process and the desired outputs. This is known as *forward mapping*.

For all research purposes, a proper understanding of these relationships help to mathematically model the process. This is possible, when we can precisely understand all the physical phenomena involved in a particular process. These physical phenomena are then converted into differential equations which are then solved with boundary conditions. In case of electron beam welding, there are so many variables involved that often it becomes highly challenging to account for all the phenomena with correct boundary conditions. Here comes the role of soft computing. In soft computing, we are not concerned about the intricacies of the physical phenomena. Here, all these phenomena are kept confined, as if, they were in a black box. Soft computing comprises of different tools which try to imitate the way human learns. Though we try to prove our intelligence, by trying to be precise by performing rigorous computations, our natural instincts are just the opposite. Over the centuries, man has learned from

- experience,
- generalized learning rules,
- recognition of patterns,
- heuristics.

These learning methods may not give rise to very accurate results but we can always counter accuracy with cost of evaluation.

Ever since its invention electron beam has been used mostly to weld highly reactive and refractory materials. These materials have strategic applications and thus, detailed techniques of welding with electron beam are mostly classified. A database needs to be generated, which will comprise of different working parameters and material properties as inputs and mechanical and metallurgical properties as outputs. To generate such a database, which contains the end and mid values of all the parameters, the experiments have to be performed in accordance with the philosophy of design of experiments. Central Composite Design (CCD) is one such tool in design of experiments, which is generally utilized in such situations.

When two pieces are welded together, the mechanical strength and metallurgical properties are found to depend upon the weld-bead profile. Some of the weld-bead profile features, which are the outputs of an experiment, are like Bead-Penetration (BP), Bead-Width (BW), Bead-Height (BH) etc. To get a desired output, one has to optimize the inputs by selecting a combination of values for various parameters within their specified ranges. It may be seen that some of the inputs may be retrograde for an output. However, when there are more than one outputs, one of the outputs may be retrograde to another. These are, then, treated as constrained optimization problem and, may be, effectively solved using a Genetic Algorithm (GA) with a Penalty approach. The optimized input parameters can be then utilized to predict outputs by different types of Artificial Neural Networks (ANNs) like Back-Propagation Neural Network (BPNN) or Genetic Algorithm tuned Neural Network (GANN). This is *forward-mapping*. This type of input to output mapping is useful for modeling. However, for all practical purposes and process automation, the *reverse-mapping* is more significant, where one is interested to know the required set of input parameters to get the desired outputs.

The energy density in electron beam welding is very high. This helps to get deep penetration welds. It is desirable in such cases to get the maximum penetration with minimum lateral heat transfer. Since the weld area has to be minimized and at the same time, the weld penetration has to be maximized, a constrained optimization tool is required.

Artificial Neural Network (ANN) is one of the soft computing tools, where the network is trained to learn, as a human does, by examples. The examples or instances of learning may not be always of the same type and often are too large in number. It will be quite humanly, in such cases, to assimilate the like instances based on some concepts of similarity. This is called *clustering* and is an important concept of *data-mining*. Clusters formed are, generally, either compact or distinct. But, there is always a need to have clusters, which are both compact and distinct at a time. These clusters, as are often in greater than three dimensions, are difficult to visualize. However, with the help of Self Organizing Maps (SOM) these higher dimensional data may be visualized in lower dimension (in either 2D or 3D) to get a feel of how compact and distinct the clusters are. In case of Radial Basis Function Neural Networks (RBFNN), too, the number of hidden neurons is, at times, determined by the number of clusters the data get divided into. The clusters, which are both distinct and compact will definitely have an edge over the other clusters, which are either compact or distinct, when utilized in the RBFNNs.

1.2 Literature Review

If two plates were to be welded together, it would be a welder's delight to see those two got joined in a single pass. Happier, still, he would have been, if the welded structure passed through the mechanical tests. To make this happen, the welder definitely has to know the inter-relationship of various machine parameters with the depth of penetration of welds, width of the weld crown, that is, the geometry of fusion zone of the weld. All these depend on the peak temperature that is achieved and the way heat travels in different directions and simultaneously the way cooling takes place in the welded parts. A proper understanding of the development of weld pool shape in EBW had always been a difficult task. Due to inherent complexity of the process, direct experimental investigations are only a few, as they are expensive to carry out. Petrov et al. [10] filmed the formation of the shape and size of the weld pool along with the keyhole, with a charged-coupled device camera, during an experimental investigation. They noticed, during such experiments, that with the increase in welding speed, the pool width decreased.

Analytical Approaches

There have been many theoretical approaches to study the effect of various physical phenomena on weld-pool shape. Modeling the formation and solidification of weld-pool had been always a challenging task, as there are too many physical phenomena to be considered.

The first pioneering work in this direction was done by Rosenthal [11] during early forties. The author, assumed the heat source to be a point of infinite intensity, which was highly unrealistic. In the year 1965, Hashimoto and Matsuda [12] propounded a formula, which related the depth of penetration, beam parameters and material characteristics. Here, Hashimoto assumed the electron beam to have a square cross-section at a constant power density. It was supposed that there was no interaction between the electron beam and metal vapor in the capillary, and that the fused peripheral zone was at the melting temperature. It was further considered that heat dissipation to the atmosphere was isotropic and that no heat was transported by convection within the fused peripheral zone. Though the last consideration was improper, nevertheless, the most difficult task in this model was to measure the focal spot diameter.

Klemens [13] considered energy balance and energy loss mechanisms to predict the penetration of the electron beam. He assumed that the penetration of the beam was mostly governed by conduction heat transfer. The cross-section of the electron beam was supposed to be sufficiently narrow with a very high energy content. The model predicted the bead penetration in both static as well as moving states of the beam. During EBW, the shape of the moving molten pool of metal is generally seen to be elliptical. Miyazaki and Giedt [14] not only explained the reason why the pool was elliptical but also derived a relationship between the weld power and weld penetration by assuming an elliptical heat source.

When Miyazaki and Giedt established the reasons for the weld pool to look elliptical, from the top view along the line of travel, they had considered the heat source to be uniformly concentrated. Eager and Tsai [15] gave information regarding the shape of the weld pool from the solution of a traveling distributed heat source. For this purpose, they assumed the heat source to be Gaussian type and that it moved on a semi-infinite plate.

It was shown earlier by Swift-Hook and Gick [16], that deep fusion by an electron beam was better represented as a line source. Vijayan and Rohatgi [17], also assumed the heat source to be linear, and described the physical nature of transient fusion and deep penetration by an electron beam in semi-infinite metal targets. They studied both the formation of transient fusion zone and also the formation of transient key-hole. In their model, they had supposed that the melting started, at a point, beneath the surface of the workpiece and then, the melt penetrated deeper into the workpiece. It was also supposed, in the model, that the line-heat source not only penetrated deep into the workpiece but also spread across the surface due to conduction. Due to this, workpiece also melted laterally. The model developed gave a good description of both transient as well as steady state fusion. The model helped to distinguish between the melting point isothermal boundary and fusion boundary of high thermal conductors in general. The model further justified the spreading of fusion layer laterally by thermal conduction, thereby, the weld-profiles were predicted.

A more realistic model was developed by Elmer et al. [18] Their model agreed with the point source solution predicted by Rosenthal. Both the point-source and the distributed-source models were based on the assumption that the heating effect was limited to the surface of the workpiece. The authors compared the geometric shapes of the EB weld pools with already established, distributed source, point source, and line source heat-conduction models. They showed that each model could represent certain EB welding regimes and that none of them could represent the entire paradigm. The authors showed that the weld pool shape depended on average energy absorbed per unit area on the surface of the work-piece and the ratio of the beam power to beam area. For energy densities greater than the critical value, the welds could be simulated both by point-source and line-source. This critical energy density which separated the different heating modes was found to be material dependent. In case of ASS 304, this was $10\ J.mm^{-2}$. Finally, the authors could develop an empirical relationships between penetration depth and EB welding parameters for the distributed, point and line source heating modes. In their model, the weld depth could be predicted, only if the weld width was known. Since the weld width could not be known *a priori*, they substituted that with the focal spot diameter. The greatest problem associated with this model was that any error in the measurement of the focal spot diameter of the electron beam, would have resulted in an erroneous relationship between welding parameters and weld depth.

Koleva et al. [19] established a correlation between weld-depth, weld-width with operating parameters like welding velocity, beam power and position of beam focus from the sample surface. In their model the authors considered a steady state model involving a linear, uniformly distributed heat source, in a coordinate system, that moved with respect to the sample coordinate system.

All the analytical models, discussed above, were based on the shape of the source, distribution of the energy of the source and the effect of the boundary conditions on the heat transmission from the source. Couëdel et al. [20] studied the sensitivity of the thermal field to the source size and the effects of boundary condition. The type of heat source considered in their study were both line source and Gaussian distributed type. In actual practice, before welding of massive sized plates, generally, the working welding parameters are tried out on smaller plates to check the full penetration. There, the width of weldment on narrow, trial-plates are seen to widen due to the over-heating. The developed analytical heat transfer model [20, 21], made it possible to estimate critical conditions of weld-bead widening. The model was equally capable to predict both the full as well as partial penetration welds. The 2D analytical solutions used vibrated and non-vibrated Gaussian cylindrical or line models of heat source. However, this model did not consider latent heat, convection heat transfer and other properties of the welded metal that were independent of temperature.

Ho [22] developed an analytical model to predict the fusion zone of an electron beam weld with a Gaussian profile of the beam, whose focal point was located either above or below the surface to be welded. The shape of the key hole cavity was assumed to be a paraboloid of revolution. The coordinate system of the moving frame for this model was assumed to be parabolic. The effects of beam focusing characteristics, such as location of beam focus relative to workpiece surface, spot size at the focus, and beam-convergence angle on fusion zone were investigated. The predicted depths of fusion-zone varied with the position of focus location and focal spot size. The penetration increased and reached maximum, when the position was found to be slightly below the top surface of the work piece, and then decreased with further descent. The penetration was found to increase with low focal spot diameter. The transverse sections of the fusion zones, as predicted by the model, were conical with a spherical cap on the top, for deep penetration, and were similar to a paraboloid of revolution in case of shallow penetration.

Rai et al. [23] developed a 3D numerical model of heat transfer and fluid flow in a keyhole mode of the EBW. The model took into account the variation of wall temperature with depth and effect of Marangoni convection on keyhole walls. Convection was the dominant mechanism of heat transfer in the weld pool and gradient of surface tension played an important role in the fluid flow. The effect of Lorentz force was found to be insignificant compared to that of Marangoni force in their model. The welding parameters, such as beam radius, input power and welding speed were seen to have significant contributions on the weld pool geometry.

There had been a few attempts [24, 25], where a correlation for joining materials under different operating conditions, in case of laser welding, was tried out with some dimensionless numbers. To establish this, Peclet (Pe) and Marangoni (Ma) numbers were utilized. It was shown that for the materials with high Prandtl (Pr) number, both Pe and Ma were high, heat was transported primarily by convection, and the resulting weld pools were shallow and wide. However, for a low Prandtl number, the resulting pools were deep and narrow. These type of work, however, have not been reported for EBW.

The developed models reported above have the following shortcomings:

1. All the analytical models discussed above are dependent on the physical characteristics of the target materials to be welded. The correct values of different physical parameters at elevated temperatures are difficult to measure.

2. In some of the models, the diameter of beam spot was also considered, whose measurement requires a special attachment to be fitted to the experimental set-up.

Soft Computing-based Approaches

It has been shown above that mathematical models can be utilized to solve problems using differential equations depicting the actual physical phenomena. Since welding is a process comprising of a number of complicated natural phenomena, all of which may not be fully understood, it may not be always possible to develop an appropriate differential equation of the said process. In such situations, models are made from the outcomes of experiments performed as per some statistical designs and then analyzed by regression methods to predict the required output. The regression equations can be either linear or non-linear. Yang and Chandel [26], and Yang et al. [27] performed both linear as well as non-linear regression analysis to model submerged arc welding process. Non-linear regression equations are generally used to model welding phenomena but it was observed by Yang et al. [27] during modeling of submerged arc welding process that linear regression equations were equally suitable. The above statistical regression analysis yielded more or less satisfactory results, while predicting the response from the process parameters. It is to be mentioned that the statistical methods are mainly global in nature, that is, the usual practice is to establish a single working relationship between the inputs and an output for the entire domain of interest, as a result of which, it might be possible to predict the results accurately at the anchor points only (that is, the points used to carry out the regression analysis). However, there might be some significant deviations in prediction at the intermediate points. To overcome this problem, Ganjigatti et al. [28] developed a new methodology to model the input-output relationships by carrying out regression analysis cluster-wise, which took care of the forecasting of intermediate points, as well.

Welding is a very complicated phenomenon and its variables generally have highly non-linear relationships with one another. Non-linearity present to this extent cannot be very well-defined by a fixed order regression equation. To overcome this, some investigators tried to model the input-output relationships using neural networks. Nagesh and Datta [29] used a back-propagation neural network to predict the bead geometries of mild steel electrodes deposited on cast iron plates. De et al. [30] used an ANN to predict the quality of welding in pulsed current Gas Metal Arc Welding (GMAW) process. Kim et al. [31] showed that neural network-based model could give better prediction of the bead-height than the empirically developed equations could do. In a similar fashion, it was shown by Lee and Um [32] that neural network could predict the bead-geometries better than the empirical relationships developed by the regression analysis did. Ping et al. [33] modified the structure of a conventional feed-forward multi-layer perceptron network with a single output instead of the multi-outputs. This type of network was named as Self Adaptive Offset Network (SAON). The authors proved that SAON could work better than the conventional networks.

Several attempts were also made by various researchers to optimize the weld-bead geometry. Tay and Butler [34] used a radial basis function to approximate non-linear dynamics of the welding process stochastically, in order to optimize the basic welding parameters.

RBFNNs are generally trained using either back-propagation algorithm or genetic algorithm. If the nature of error surface is unimodal, BPNN may outperform GANN, whereas for a complicated and multi-modal error surface the latter may perform better than the former [35, 36]. Benyounis et al. [37] used Response Surface Methodology (RSM) to predict weld profile in laser welded medium carbon steel. Central Composite Design (CCD) is one of the most important experimental designs used in process optimization studies. It is a design used in RSM to build a second order quadratic model. Gunaraj and Murugan [38, 39] performed experiments with submerged arc welding of stainless steel pipes based on CCD with four factors, each of them set at its five levels to predict bead-geometry parameters.

Taguchi [40] developed a method of conducting experiments based on orthogonal array, which gave a much reduced *variance* for the experiment with optimal setting of control parameters. This method showed the amalgamation of design of experiments with optimization of control parameters to obtain the best results. Orthogonal arrays provided with a set of well balanced (minimum) experiments and signal-to-noise ratios served as the objective functions for optimization. Taguchi method was utilized by Tarng and Yang [41] to analyze the effect of each welding process parameter on the weld-bead geometry. Based on the concept of signal-to-noise ratio and analysis of variance, the set of optimal welding process parameters was obtained and verified. Tarng et al. [42] used a Grey relational analysis to investigate multiple performance characteristics in the Taguchi method for the optimization of submerged arc welding process. It was shown in the study that the use of the above approach greatly simplifies the optimization procedure for determining the optimal welding parameters with multiple performance characteristics in the submerged arc welding process. Gunaraj and Murugan [43] minimized weld volume for the submerged arc welding process using an optimization module that was available in Matlab.

Genetic Algorithm (GA), introduced by J. H. Holland [44], is a population-based search and optimization tool. The GA works equally good in either continuous or discrete search space. It is a heuristic technique inspired by the natural biological evolutionary process comprising of selection, crossover, mutation etc. Vasudevan et al. [45] used a GA to achieve the target bead geometry in Tungsten Inert Gas (TIG) welding by optimizing the process parameters.

In a GA, when the search space is large and the objective functions are too complicated, its computational time increases drastically and it is difficult to get solution in real-time. To overcome this difficulty, Kumar and Debroy [46], and Mishra and Debroy [47] showed that multiple sets of welding variables capable of producing the target weld geometry could be determined in a realistic time frame by coupling a real-coded GA with a neural network model for gas metal arc fillet welding.

As the welding process is inherently non-linear the regression equations can predict effectively in a very narrow region of the variables. If the search space is large, the model may lose its effectively. Kim et al. [48] used a GA and response surface methodology simultaneously to find a set of welding process variables that could produce the desired weld-bead geometry in Gas Metal Arc Welding (GMAW). As a GA was used for initial optimization, the presence of some bad data in the search space, did not affect the model. The response surface methodology used the near-optimal values as a reference point to obtain a model of the welding process and determined optimal values of the process variables.

Correia et al. [49] adopted a similar approach, where a GA was used as a tool to decide near-optimal settings of a GMAW process. The search for the near-optimal settings was carried out step by step with the help of a GA by predicting the next experiment based on the previous, and without using the knowledge of the modeling equations between the inputs and outputs of the GMAW process. The GA was able to locate near-optimal conditions, with a relatively small number of experiments.

In a GA, equal number of search points are generated in every iteration. Thus, the computational complexity remains till the GA converges. Kim et al. [50] developed an approach similar to the GA, known as Controlled Random Search (CRS), which performed the search based upon a set of initial search points but in the subsequent iteration, the search would narrow down to lesser number of search points.

Clustering

Here, we try to bring similar points together and group them accordingly. This process of grouping like data points is known as clustering. It is one of the most important tools for data mining. Thus, clustering of the data based on the principle of similarity makes a sense. Similar data (decided using the concept of distances among them) are grouped into one cluster and dissimilar data may belong to different clusters. The boundaries of the clusters may be either rigidly defined or vaguely defined, and accordingly, the clusters are called hard clusters or fuzzy clusters respectively. Amongst different types of clustering techniques, one of the most popular one is Fuzzy C-Means (FCM) clustering algorithm. This was proposed by by Dunn [51] and implemented by Bezdek [52]. It is one of the most popular fuzzy clustering algorithms. It is an un-supervised way of data clustering, where noise (if any) may also get clustered. To prevent this problem, a semi-supervised learning was preferred instead of un-supervised learning. To tackle this, Zigkolis and Laskaris [53] developed a conditional *FCM* (CFCM) algorithm. In this algorithm, a dissimilarity measure (expressed in terms of euclidean distance) was minimized for the data points in the pre-defined clusters. There are, however, different instances, where euclidean distance was replaced by exponential function [54], weighted linear regression distance [55], weighted euclidean distance [56], Mahalanobis distance [57]. It is seen that there had been many variants of the basic FCM algorithm. Quadratic terms or entropy terms were added to the objective function of the basic FCM to cater to specific needs. Ichihashi et al. [58] proposed a *generalized FCM* clustering method, which generalized the basic objective function of FCM, so that by changing the coefficients of objective functions either *quadratic function*-based FCM or *entropy term*-based FCM could be attained.

The effect of dimension, however, could not be removed by all these algorithms. Another distance-based approach was proposed by Zhang et al. [59], which could reduce the effect of dimensions. Han et al. [60] utilized Bayesian likelihood fitness function in place of euclidean distance. The algorithm was named as Modified Fuzzy C- Means (MFCM). Application of MFCM resulted into viable solutions for various problems of nonlinear blind channel equalization.

In spite of its wide popularity and applications, FCM algorithm has the following inherent demerits: *i)* clustering results in FCM are un-satisfactory for uneven sample distribution, *ii)* its solutions often get trapped into a local minima, *iii)* its solutions depend upon the initial values of the FCM parameters selected. To overcome these limitations, a novel fuzzy clustering algorithm based on *Chaos Optimization* (FCCO) was proposed by Li et al. [61]. This algorithm combines mutative scale chaos optimization strategy and gradient method. Wang and Fei [62] had come up with an algorithm called *Multiscale FCM* (MsFCM) to scan MR images. Another problem with the FCM algorithm lies in the fact that it cannot handle data, where the boundaries between the clusters were non-linear. Song et al. [63] proposed a Fuzzy C-Means algorithm with a *Divergence-based Kernel* (FCMDK). The FCMDK worked based on the FCM algorithm and divergence-based kernel method. In this method, data were transformed from the input space of higher dimension to feature space of lower dimension before applying the clustering techniques. This helped to solve complex non-linear problems.

In the field of image analysis also, FCM algorithm could classify most of the noise-free real-images with an uncertain and complex data distribution. However, as FCM algorithm does not incorporate spatial information, it fails to segment image corrupted by noise and other imaging artifacts. Oh et al. [64] used a weight determined based on the entropy obtained from the neighboring pixels in the FCM algorithm, and the number of optimal cluster was determined utilizing the intra-cluster distance in the coded image based on the clustered pixels for each color component. Kang et al. [65] developed *Adaptive Weighted Averaging FCM* (FCM-AWA) algorithm to tackle this type of problem.

It is a known fact that the time of convergence of a fuzzy clustering algorithm is too high, as the cluster centers are iteratively determined. Yao et al. [66] proposed a novel approach, where the algorithm automatically detected the number of clusters and their centers. This algorithm was named as *Entropy-Based Fuzzy Clustering* (EFC).

Palanisamy and Selvan [67] developed an entropy-based fuzzy clustering method to identify relevant subspaces in the functional workspace. A heuristic method based on the Silhouette criterion was used to find the number of clusters. Hence, the fuzzy entropy reflects more information on the actual distribution of patterns in the subspaces.

1.3 Gaps in the Literature

After reviewing the available literature, the following shortfalls are detected:

- There have been instances where different soft computing techniques have been utilized to predict the bead-geometries. Some attempts have also been made to minimize the weld-bead volume. However, in order to maximize weld strength, the penetration should be maximized provided the microstructure of the weld and heat affected zone remain the same. No such attempt has been reported, where this type of constrained optimization problem has been solved.
- The shapes of weldment have been predicted using various analytical approaches. However, there have been only a few attempts for the same using the principle of soft computing. Moreover, no study has been reported to predict complete bead profile of electron beam welding.
- Clustering techniques available in the literature make clusters of the data-set that are either compact or distinct in nature. However, clusters are to be compact and distinct too. No such clustering technique has been reported, which can fulfill both the requirements.
- Literature review shows various clustering techniques with the help of which the number of hidden neurons of a radial basis function neural network (RBFNN) can be determined. It is to be noted that the performance of RBFNN may be dependent on the number and nature of clusters made by the algorithm. Not much study has been reported in which optional clusters have been obtained along with other parameters of the RBFNN to improve its performance.

1.4 Aims and Objective

After looking into the gaps in the available literature, the aims and objective of the present thesis have been set as follows:

1. **Optimization of Welding Parameters to Minimize Weldment Area but to Maximize Penetration:** When two pieces are joined together, the process is said to be successful if it can be done across their entire thickness. The efficiency of energy expended in welding will be maximized, if the entire energy can be utilized to get full penetration

with a minimal energy dissipating across. The resulting weld-profile should have maximum penetration but minimum width, resulting into a minimum weldment area. As the shape of weld-profile in case of EBW is dagger-like, it is difficult to determine the area of the weldment. As the weld-profile is a function of various welding parameters, they need to be optimized keeping the above constraints in mind. To achieve such a constrained optimization, the following steps have been identified:

Step 1: Bead-on-plate EB welding on the concerned material will be performed. Experiments will have to be conducted according to a design of experiments, say Central Composite Design (CCD) to study the effects of inputs on the outputs.

Step 2: As output of the experiment, the weld-profile geometries will be measured along with its micro-hardness values. The weld-profile will be assumed to be made up of three 3^{rd} order curves. The end points of the curves will be visually identified and their coordinates will be noted. Each of the responses (outputs) will be modeled as a function of the input independently, using statistical regression analysis.

Step 3: The area of weld-profile will be determined after obtaining the coefficients of the curves. The area under the curve can be minimized, while maximizing the penetration using a GA with a *Penalty* approach.

2. **Bead-Profile Prediction:** The outputs of the experiment, that is, the coordinates of the end points of the fragmented curves can be utilized to train Neural Networks. The error in prediction may be minimized using:

   (a) back-propagation algorithm,

   (b) genetic algorithms.

   The trained networks may then be utilized to predict the bead-profiles for some test cases.

3. **Clustering of Input-Output Data:** An attempt will be made to group a huge data set of multi-dimensional information into some clusters, in such a way that the clusters become both compact as well as distinct. Existing clustering techniques yield either compact or distinct clusters. A clustering algorithm will be developed, which will give both compact and distinct clusters.

4. **Forward and Reverse Modeling using a Radial Basis Function Neural Network:** In forward modeling, outputs will be expressed as the functions of input variables; whereas the reverse is attempted in reverse modeling. Both the forward as well as reverse modelings will be carried out using RBFNNs to establish input-output relationships of EBW process conducted on two different materials. The number of hidden neurons will be decided based on the the number of clusters made on the data-set using some clustering algorithms. Besides two conventional fuzzy clustering algorithms, one

newly developed algorithm will be utilized to cluster the input-output data of the said process.

1.5 Contributions Made by the Scholar

The scholar has made the following contributions in the present thesis:

- BOP welding experiments were carried out on ASS-304 plates and Al-1100 plates using a 24 kW Electron beam welder at Bhabha Atomic Research Center, Mumbai, India.
- A GA with a penalty approach was successfully implemented to solve constrained optimization problem of minimizing the weldment area after keeping a maximum weld-bead penetration.
- The dagger-like shapes of the weldment were successfully predicted for various welding parameters using BPNN and GANN.
- A modified clustering technique was established from two existing techniques of the same, which could yield both compact as well as distinct clusters.
- Both forward and reverse modelings were successfully performed using RBFNNs for ASS-304 and Al-1100 data.

1.6 Layout of the Thesis

This thesis contains eight chapters. The contents of Chapters 2 through 8 are stated below in brief.

- **Chapter** 2 **:** It introduces the tools and techniques used in the present thesis.
- **Chapter** 3 **:** It deals with a detailed description of the experimental set-up, the scheme behind scheduling the experiment, the process of data collection.
- **Chapter** 4 **:** This chapter concentrates on the detailed statistical regressional analysis on the collected data.
- **Chapter** 5 **:** This chapter focuses on the techniques used to optimize the bead parameters and for prediction of weld-bead profiles.

- **Chapter** 6 **:** It deals with clustering of input-output data-sets of the said welding process.
- **Chapter** 7 **:** It concentrates on forward and reverse mappings of EBW process using RBFNNs.
- **Chapter** 8 **:** Some concluding remarks are made in this chapter and the scope for future work has been indicated.

1.7 Summary

This chapter starts with an introduction to electron beam welding process. A thorough literature review is then carried out. The shortfalls of the available literature have been identified. The aims and objective of the present thesis have been stated, followed by the contributions of the author and layout of the thesis.