INTELLIGENT WELDING OF MATERIALS

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1. Introduction

As welding technology improves, industry is incorporating more types of automatic welding equipment. One of the most important approaches being used is called intelligent automation for welding technology. This approach combines automatic welding equipment, the knowledge of human experts, and Artificial Intelligence (AI). An intelligent welding machine is the one equipped with sensors, artificial intelligence and actuators to sense and control welding operations in real time. Developing smart or intelligent welding machines can reduce the occurrence of defects in welds. Intelligent welder is differentiated from a mere mechanised or pre-programmed welder in that it controls the quality of the weld directly rather than simply maintaining the welding parameters within specified limits of the values based on experience and/or trial welds.

Intelligent sensing and control is a multi-disciplinary approach that attempts to build adequate sensing capability, knowledge of process physics, control capability, and welding engineering in to the welding system such that the welding machine is aware of the state of the weld and knows how to make a good weld [1]. The sensing and control technology should reduce the burden on the welder and guide the welder to eliminate errors while providing the adaptability needed to accommodate the variability found in the welding industry. In real-time control applications, an artificial intelligence (AI) technique can be used to generate a control action directly. Figure 1 shows the use of two of the AI techniques, image processing and expert system in an intelligent welding system.

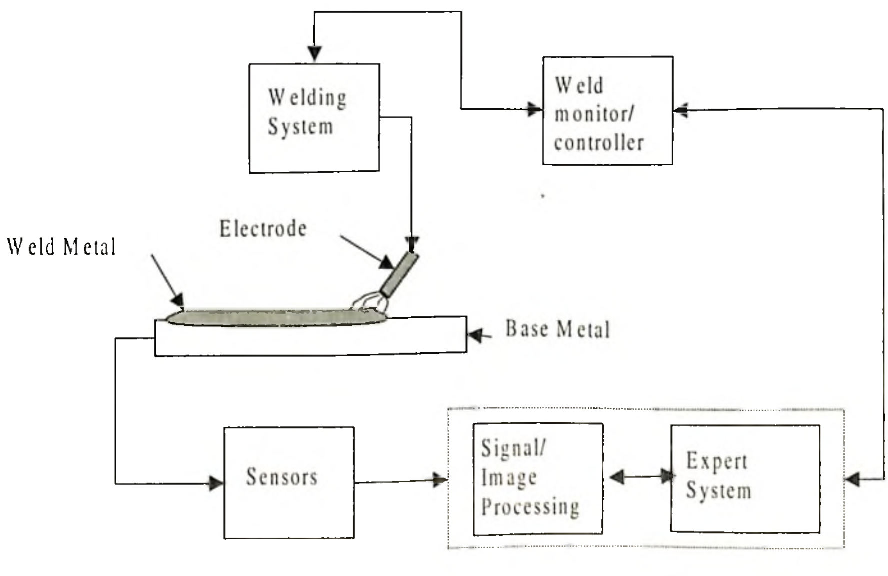

Figure 1: Schematic diagram of an Intelligent Welding System

The various methods of AI that can be applied to welding include expert systems, image processing, intelligent database systems, signal analysis, artificial neural networks, and fuzzy logic systems. While expert systems and fuzzy logic-based systems model expert's knowledge, neural networks follow the approach to learn task correlations from examples and experimental data without the need to interview the expert. Artificial neural network is a mechanism for generating an input to output mapping function given a set of discrete data points. Expert systems and fuzzy logic systems both differ from artificial neural networks in that they use conditional logic statements as the input data. The difference between these two methods is that expert systems normally give yes/no types of output, whereas fuzzy logic systems admit degrees of may be or levels of grey as outputs. To reduce the disadvantages of the individual methods, individual processes can be combined with each other. These so called hybrid methods are receiving considerable attention from research community because of their tremendous potential for commercial exploitation.

2. Expert Systems

Expert system technology is a branch of artificial intelligence that has gained new respectability, partly due to the fact that the computers have the speed and memory capacity to cope with the expert system techniques that are typically slow and memory intensive. Expert systems have the power to reason in a similar way to human experts, which has enabled them to solve extremely complex problems. Also they have the ability to cope with uncertain data, and still recommend a course of action. These characteristics are drastically different from those of conventional softwares, whose problem solving capabilities are strictly limited to algorithmic applications.

2.1 Definitions of expert system

An expert system is an intelligent computer program that uses knowledge and inference procedure to solve problems that are difficult enough to require significant human expertise for their solution [2]. The knowledge necessary to perform at such a level plus the inference procedure used can be thought of as a model of the expertise of the best practitioners of the field.

2.2 Structure of an expert system

An expert system can be considered to consist of three components. A knowledge base, an inference engine and a user interface (Fig. 2).

2.2.1 Knowledge base

The knowledge base is the memory component of the system. It stores all the information given by both the programmer during the system development, and the user. Thus, the knowledge base itself is split into two parts: the static rule base and the dynamic fact base. The former contains all the subject information collected by the programmer from books, journals and human experts. This information is stored in the form of rules and questions. The dynamic fact base holds all the data given by the user during the program's operation.

2.2.2 Inference engine

The inference engine is that component of an expert system that acts on the knowledge base, deciding which questions should be asked and which rules to invoke. This component operates upon the knowledge base to build expert reasoning. It controls and executes this reasoning towards specific problems. Inference engines operate in many different ways, depending upon the formal logic that underlies them and the control strategies employed.

2.2.3 User interface

The third component of an expert system is the user interface, which is the communications link between the programme and the user. At its most basic level, it is only what the user sees on the video monitor

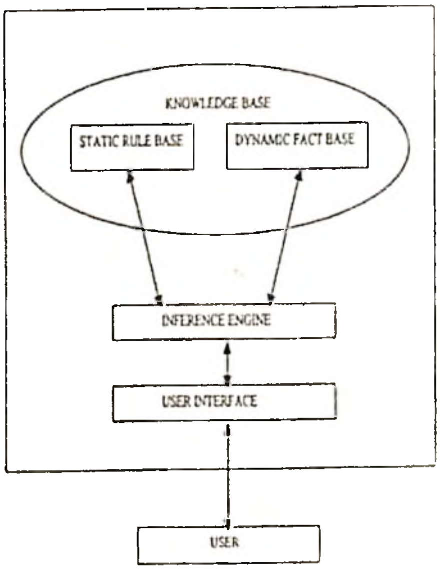

Fig. 2: The structure of an Expert System

2.3 Expert systems in welding

Several expert systems have been successfully developed and implemented in the welding industry. Few of them are listed below and the one on ferrite prediction is described briefly.

2.3.1 Ferrite predictor expert system

The expert system is being developed in our laboratory at the Indira Gandhi Centre for Atomic Research (IGCAR) Kalpakkam. This software uses the Schaeffler, DeLong, and WRC-92 diagrams for predicting the d-ferrite in austenitic stainless steel welds. Using C++ graphics, program was written to view these diagrams on the computer screen. The nickel and chromium equivalent formulae for the respective diagrams were included in the program. Once the user enters the chemical composition of the weld, then the program displays the list of diagrams available to determine the ferrite number. If the user selects a particular diagram, the program calculates the respective chromium and nickel equivalents and displays it on the screen. Once the user asks for the diagram, it displays the respective diagram. On the diagram a marker, points out the exact ferrite number for the input chemical composition. On request, and the solidification mode are displayed in the results. The three constitution diagrams can be displayed independently with a window displaying the ferrite number. Hidden iso-ferrite lines were introduced in the constitution diagrams to estimate d-ferrite or ferrite number in closer intervals than it is available in the standard diagrams. This software is being developed to incorporate data base of stainless steels, AWS classified filler metals, knowledge base about stainless steels, their mechanical and corrosion properties. The system will be further improved to allow for modification of composition or dilution interactively on the diagram and instantaneously view the effect on ferrite content

Table 1: Expert systems used in welding

No.	Expert System
1	Welding procedure selection expert system
2	Welder qualification test selection expert system
3	Weld defect diagnosis expert system
4	Weld estimating expert system
5	Weld scheduler expert system
6	Weld costing system
7	Naval expert welding control system (NEWCS) [3]
8	Weldex
9	SAW expert system
10	An expert robot welding system [4]
11	Expert system for on-line process optimisation in GMA welding [5]
12	Expert system in electron beam welding [6]
13	Expert system for generating welding procedures of boilers & pressure vessels [7]
14	Welding cracking prediction and diagnosis expert system [8]

Some of the expert systems used in welding practice are given in Table 1.

3. Fuzzy Logic Systems

Fuzzy logic is an extension of binary logic and allows representation of fuzzy knowledge by determination of membership values for linguistic values of linguistic (qualitative) variables. Fuzzy logic refers to multi-valued logic that includes not only the conventional two-valued, true/false crisp logic, but also the logic of three, four or more values. This means we can assign logic values of true, false and somewhere in between.

The stages involved in fuzzy logic control are:

(1) Input crisp data from sensors.

(2) Fuzzify the data using the membership functions.

(3) Application of the fuzzy rules to determine memberships of the output functions.

(4) Defuzzification of the output functions to determine crisp output.

(5) Outputting the crisp value to the control system.

The fuzzy logic designers' task is to derive the membership function for the input and output variables and to generate the fuzzy rules. The rule generation can be done intuitively as the system is processing data whose values belong to classes which can be easily understood i.e. large, small, fast, slow etc.

3.1 Fuzzy logic systems in welding

Today a number of power sources in the market employ digital control concepts. Power sources are also available which implement the control strategy using fuzzy logic. This approach facilitates the development of advanced and intuitive control strategies than would be available using traditional coding techniques. It is claimed that by using digital and fuzzy logic control the power source will automatically adjust the arc voltage by detecting the short circuit frequency, to accommodate variations in surface condition, tip to work-piece distance and travel speed. Some of the fuzzy logic systems used in welding practice are given in Table 2.

Table 2: A few fuzzy logic system used in welding

No.	Fuzzy Logic System
1	A fuzzy algorithm in process monitoring of arc welding [9]
2	Seam tracking control by fuzzy logic in pulsed gas metal arc welding [10]
3	Recent developments & trends in quality control technology for resistance welds [11]

4. Neural Networks

Neural Networks are computer systems that emulate the neural reasoning behaviour of biological neural systems (e.g. the human brain). Neural networks consist of a series of nodes and weighted connections that when presented with a specific input pattern can associate specific output patterns. It is essentially a highly complex, non-linear mathematical relationship. Neural networks address problems that are often difficult for traditional computers to solve such as pattern recognition. One of the most significant strengths of neural networks is their ability to learn from a limited set of examples. Once, trained, the neural nets can be used to predict and/or forecast results from the new input data. The advantage of the neural network approach is that a solution can be found for a problem without knowing the internal structure of the problem. Neural networks can find a good solution for yet unknown combinations of input values.

The generation of the neural network requires

(1) Defining the input/output topology of the network

(2) Selecting the number of hidden layers and the number of neurons in each hidden layer

(3) Selecting the weights in the neural network

(4) Training the network to adjust the weights using a training set consisting of correctly classified input/output pairs.

(5) Testing the network with data that had not been used for training to determine the effectiveness of the network.

Neural networks for welding applications are now emerging as an alternative means of making "intelligent" decisions on a computer [12]. Unlike their better-known contemporaries, neural networks are designed to directly simulate the operation of the human brain, and thereby, to improve decision-making. This is achieved by applying weighted factors to each of the elements that influence a decision. These are then linked together to form the network. Software packages for building neural networks are advancing rapidly, but considerable issues about the training and programming of practical networks are still to be resolved.

4.1 Neural network model for predicting ferrite number in stainless steel welds

Predicting the ferrite content in stainless steel welds is important in order to assess an alloy's susceptibility to hot cracking and to estimate the as-welded properties. A neural network analysis has been applied for the prediction of ferrite number in stainless steel arc welds as a function of weld composition. The steps involved in developing this neural network model are: (i) identify input and output variables; (ii) identify optimum number of hidden nodes; (iii) identify initial weights that yield the best net; and (iv) evaluate the predictability of the network. The model uses 13 element concentrations as inputs that are C, Cr, Ni, Mo, N, Mn, Si, Fe, Cu, Ti, Nb, V and Co. Output is the ferrite number. In this case a feed-forward network with a back-propagation optimisation scheme has been used. The model was trained with the available data from the literature (923 data). The data covered a range of ferrite numbers from 0 to 100 with a corresponding wide range in composition. This neural network architecture consists of input nodes, one hidden node and one out put node. The input node consists of 13 elemental compositions and the out put node represent the ferrite number. The number of hidden nodes has to be optimised for maximum accuracy. This was done as follows. The data-engine neural network package was used in the present investigation. The whole data set (923 data) was split randomly in to training data set, test data set and recall data set. Then the data was normalized in the range 0–1. The weights were chosen randomly. The hidden nodes were varied from 1 to 20 to minimize the RMS error for the test data set. About 60 different combinations of weights and the hidden nodes were used to identify the optimum network. The final neural network architecture with minimum RMS error for the test data was identified as one having 13 input nodes, 6 hidden nodes and one out put node. The optimum neural network architecture is shown in Fig. 3. This model predicts the amount of d-ferrite with a better accuracy. This model will be integrated with the software for predicting the d-ferrite using the constitution diagrams.

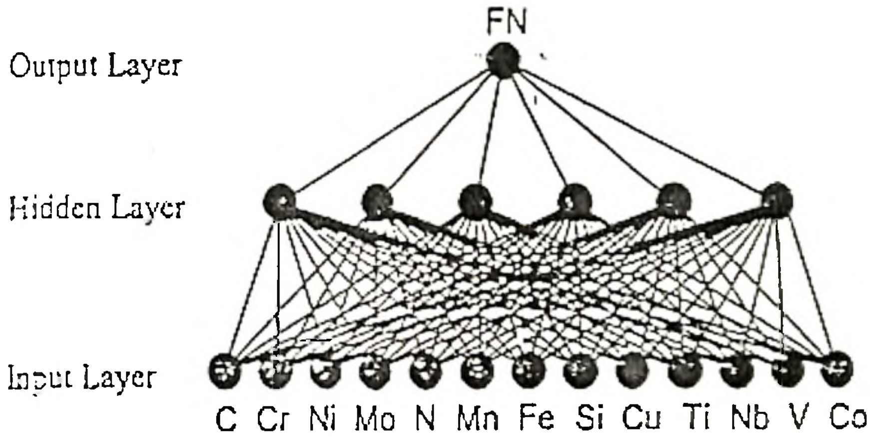

Fig.3: Optimum neural network architecture for ferrite prediction

Some of the neural network models used in welding practice are given in Table 3.

5. Hybrid Methods in welding

By the integration of different AI methods, the disadvantages of the individual methods can be reduced and substantially efficient systems can be developed. Expert systems have the ability to represent the factual knowledge but not conceptual knowledge. Learning ability does not exist for expert systems. Until they are combined with neural networks, expert systems can only be used to represent a human's factual knowledge. While expert systems perform well when dealing with crisp information i.e. where the fact is either true or false this can cause problems in automated system when an input oscillates around a threshold value. In fuzzy logic to overcome these problems rather than input values belonging to single input class i.e. greater than threshold or less than threshold, they can be assigned to multiple classes with a different membership function. Neural network models work well if the training data cover the whole problem space. Hence, the necessary data for training can become too extensive. If the training time has been too long, over-fitting may occur and will lead to a reduction of the generalization ability of the neural network. While the combination of fuzzy logic with neural networks allows, based on expert's knowledge, the definition of structure as well of the initial weighting of the neural network. This leads to substantial reduction of necessary training data sets and of training time. Hybrid methods are proving more efficient than the individual AI systems. Some of the hybrid systems used in practice are given in Table 4

6. Current Status in India

As part of the Department of Science and Technology (DST) project on Intelligent Processing of Materials (IPM), work has been carried out on the use of NDT techniques such as acoustic emission (AE) and thermography for the study of resistance spot welding and narrow gap welding, and also foe end gap welding, spacer pad welding and bearing pad welding processes employed for critical nuclear fuel sub-assembly components, in collaboration with Welding Research Institute (WRI), Tiruchirapalli and Nuclear Fuel Complex (NFC), Hyderabad [38].

6.1 Narrow gap welding

In this study, carbon steel plates of length 1000 mm, width 100 mm and thickness 40 mm were machined to have a "U" groove. CO_2 welding was carried out inside the groove. AE and thermography

Table 3: Neural network models in welding

No.	Neural Network Model
1	Estimating optimal welding parameters using artificial neural network technology [13]
2	Nugget size sensing of spot weld based on neural network learning [14]
3	Gas metal arc penetration welding development utilizing neural nets [15]
4	Modelling and optimising of a MIG welding process-a case study using experimental designs and neural networks [16]
5	Problems of predicting the quality and controlling weld formation during welding using neural network models [17]
6	Modelling of weld metal properties as a function of weld metal composition [18]
7	Neural network modelling of temperature distribution for control of gas metal arc welding [19]
8	Modelling of weld metal properties as a function of weld metal composition [20]
9	Control of weld pool width and cooling time in TIG welding using a neural network model [21]
10	Characterization and real-time measurement of geometrical appearance of the weld pool [22]
11	Impact toughness of C-Mn steel arc welds—Bayesian neural network analysis [23]
12	Artificial neural networks applied to process modelling for robotic arc welding [24]
13	Ultrasonic welding control using artificial intelligence (neural networks) [25]
14	A neural network approach to the prediction of submerged arc weld metal chemistry [26]
15	Measurement of molten pool shape and penetration control applying neural network in TIG welding of thin steel plates [27]
16	Using AI-methods for parameter scheduling, quality control and weld geometry determination in GMA-welding [28]
17	Neural network-based resistance spot welding control and quality prediction [29]
18	Modelling gas metal arc weld geometry using artificial neural network technology [30]

techniques have been used to monitor the process. Analysis of the AE signals during the three phases of welding indicated that it should be possible to monitor the welding process. Analysis of thermal images indicated that it is feasible to map the thermal wave fronts from isothermal contour movements as the arc moves along the gap. The thermal distribution and its variation with time provides the required input for model based evaluation of residual stresses, which in turn helps in optimising the welding process for obtaining weldments with minimum residual stresses.

6.2 Evaluation of resistance spot welds by acoustic emission, thermography and fuzzy logic assessment

In this study, AE and thermography techniques were used for on-line monitoring of resistant spot welding process. In addition, other online approaches such as the use of the variations in dynamic resistance with fuzzy logic approach have been attempted on the data of resistance spot welding generated at WRI, Tiruchirapalli.

A number of carbon steel sheets of approximately 1.6 mm thickness were spot welded by making use of 45-kVA capacity portable spot welding machine. Spot welding trials were carried out at different welding conditions (representing struck weld, good weld and splash weld conditions) by adjusting the phase shift setting and the weld time. Figure 4 shows the variation of RMS voltage of the AE signal with time for good weld and bad weld. Figure 5 shows the thermal image of a good weld and that of the weld made with a reduced current. Analysis of a number of welds indicated that the heat distribution in a good weld is uniformly and symmetrically distributed about the centre of the weld, whereas bad welds have irregular thermal pattern.

For implementation of the fuzzy logic control, both nugget diameter and dynamic resistance were graded as small, medium and large with triangular membership function. The quality is graded as very poor, poor, good and very good. Based on the software developed at the Indian Institute of Technology (IIT) Madras, a fuzzy estimator for the above experimental data has been arrived at. Systematic studies showed that the experimental value

Table 4: Hybrid systems in welding

No.	Hybrid Systems
1	The role of intelligent systems in weld process control [31]
2	Self-learning fuzzy neural networks and computer vision for control of pulsed GTAW [32]
3	Development of an intelligent system for cooling rate & fill control in GMAW [33]
4	A neural network/fuzzy logic system for weld penetration control [34]
5	Controlling resistance spot welding using neural network and fuzzy logic [35]
6	Application of artificial intelligence techniques to resistance spot welding [36]
7	Automatic setting of arc voltage using fuzzy logic [37]

of the quality index is in agreement with that predicted by the fuzzy estimator.

6.3 Artificial neural networks applied to evaluation of resistant spot welding process

The process variables considered are the dynamic resistance, nugget diameter and the percentage load. From the data generated, a database of 20 points has been screened during the training process. First 15 point were used for training and the rest 5 points were use to predict. The optimum network architecture has been arrived with 20 hidden nodes. The number of cycles required was 30000. The optimum value of learning rate is 0.00013 and momentum rate is 0.5. The maximum deviation in the percentage error is about 5% for the trained data and 3.23% for the predicted data.

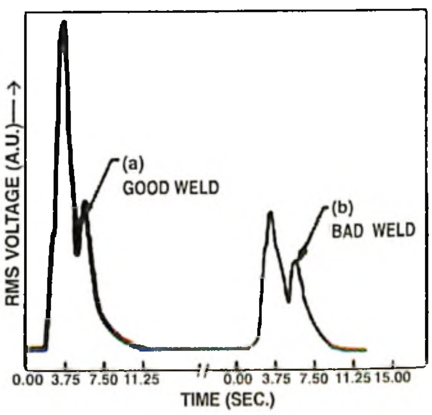

Fig.4: Variation in AE RMS voltage with time for (a) good weld (b) bad weld

6.4 Weld monitoring of nuclear fuel element components

6.4.1 End cap welding

End cap welding is used for welding of nuclear fuel elements. The AE signals generated during the welding stage as well as during the post-weld stage were also found successful to discriminate normal welds from welds with presence of defects. Higher acoustic activity was generated for tubes welded with presence of various defects as compared to the AE generated during welding of tubes without any defects i.e. normal weld (Fig. 6) The AE signals generated during welding stage as well as during the post-weld stage were also found successful to discriminate normal welds from welds with presence of defects. It has been observed that two separate clusters (normal welds and welds with presence of defects) are formed corresponding to the two weld categories. Thermal

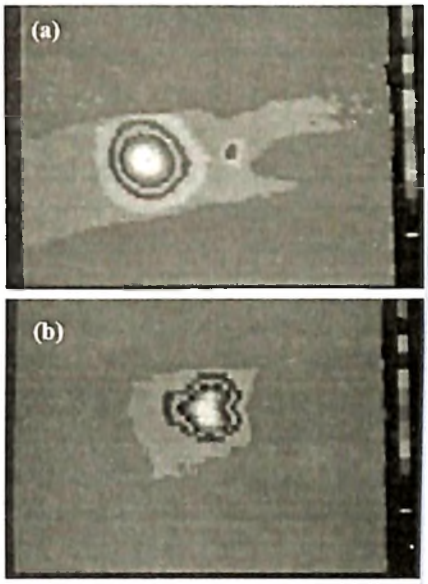

Fig. 5: Thermogram of (a) good weld, and (b bad weld

imaging carried out on thes elements after the welding proces indicated that it is possible to detec most of the imperfections ver confidently. In general good weld are characterised by uniforr isothermal widths and symmetric isothermal patterns (Fig. 7a) whil bad welds are characterised b uneven isothermal widths an patterns (Fig. 7b). By thermograph the circumferential location wher the defect had occurred could als be indicated.

6.4.2 Spacer pad welding

AE generated during the spac pad welding was correlated wi weld quality. A combination of A parameters such as: (a) initial coun and energy upon start of weldin (b) cumulative counts and energy f the complete weld cycle includir their values; and (c) counts ar energy generated only during t welding stage, were identifie Figure 8 shows the master pl [(cumulative energy – initial energ vs. (initial energy/cumulati energy)] for different types of welds. It can be seen that normal double coin welds form clusters in the both upper and lower regions of the plot while the single coin welds fall in the central region. The low pressure welds form cluster in the central region. It is also seen that the defective welds comprising both single coin welds and welds made with low-pressure fall in the high side of the energy ratio. Thus, the different categories of welds namely normal double coin weld, single coin weld and welds made with low pressure can be clearly distinguished using different parameters of the AE signals.

.4.3 Bearing pad welding

AE activity generated during earing pad welding of the normal welds and welds with high current ave shown that higher AE counts re generated during welding of the earing pads with high current as ompared to normal weld. Variation f total counts generated with total rength values of the welds has also ndicated the feasibility of istinguishing normal welds and elds with high current (Fig. 9).

. Conclusions

Artificial Intelligence methods are nding applications in intelligent ensing and control of the welding rocess that involves controlling oth the desired operation of the ocess and the properties of the oduct. Due to the long experience welding, extensive knowledge is t hand. Data for the development self-learning systems already ist. Data can be generated quickly necessary. These research efforts vill in future lead to the increased

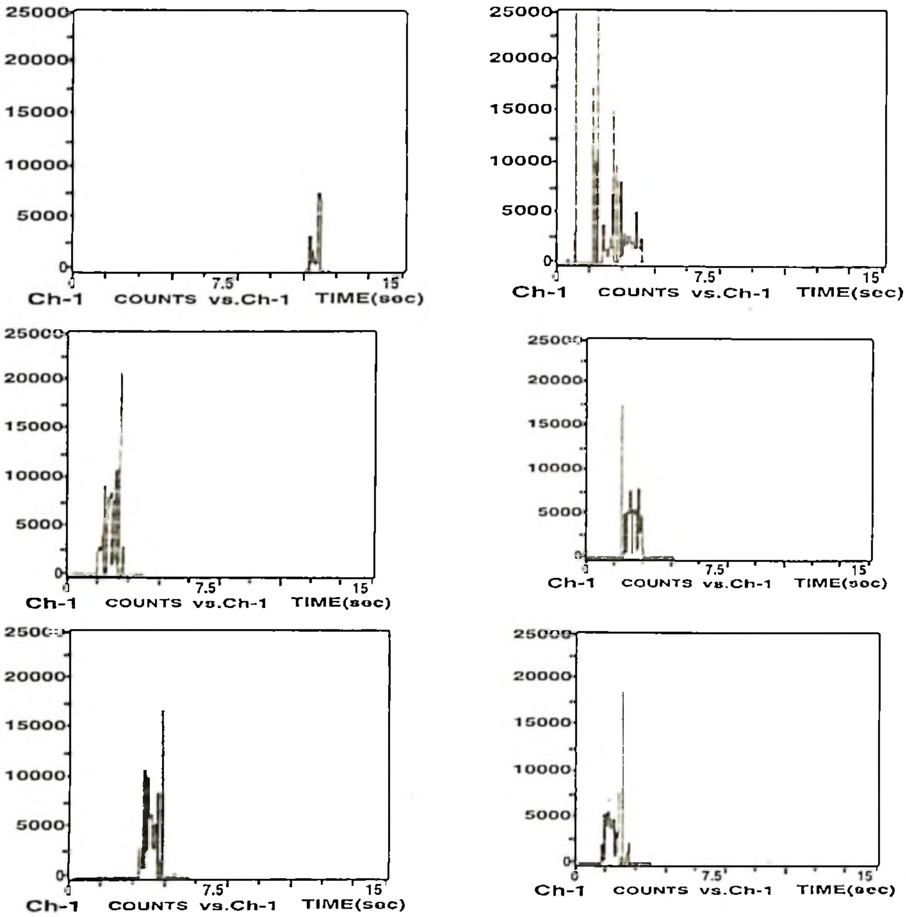

Fig. 6: AE counts observed during end-cap welding with defects and variation of weld parameters.

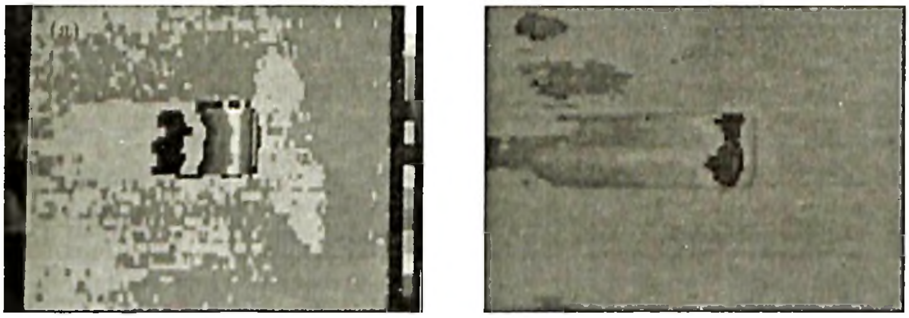

Fig. 7: Thermal image of (a) normal weld, and (b) weld with excess graphite coating

application of AI methods in automated welding. Neural networks have the capability to dynamically model the relationship between input and output parameters in the complex and highly non-linear welding process. Combination of the neural network, with its mapping and pattern recognition capabilities and a fuzzy logic controller with its ability to handle vague and imprecise data is likely to offer greatest benefits in overcoming the limitations of existing control systems.

The work carried out under the DST project on IPM has shown the feasibility of on-line monitoring of

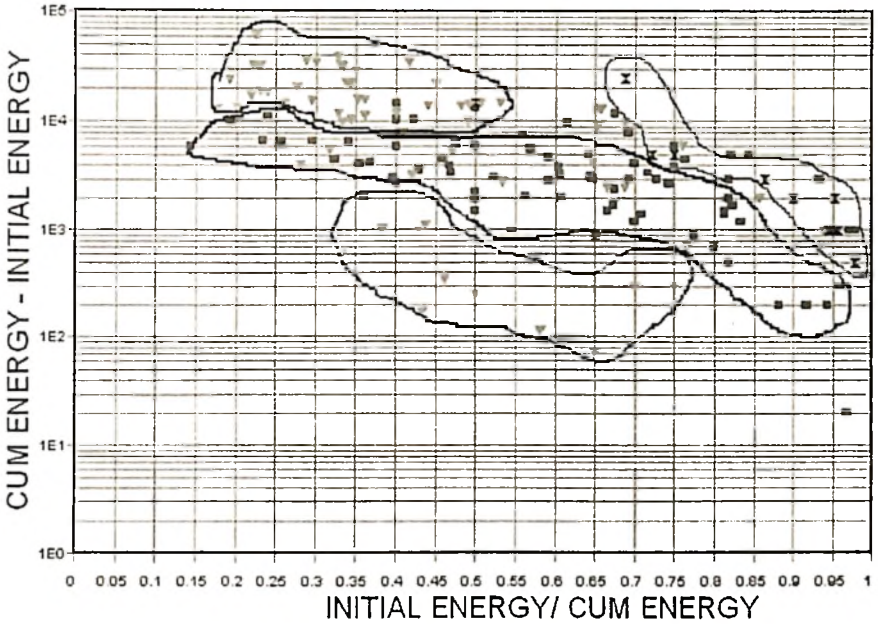

Fig. 8: Variation in (cumulative – inital AE energy) with AE energy ratio for spacer pad welding (υ Coin removed; Doubli coin; 6 Low press)

welding processes. Realising the great potential AI techniques hold for the Indian industry, the DST funded a mission project on IPM. IGCAR Kalpakkam piloted this project in collaboration with private industry. Under this project work has been carried out to develop neuro-fuzzy model for controlling the resistance spot welding process in collaboration with WRI, Tiruchirapalli and IIT Madras. After successful completion of the Phase–I of this project, the Phase–II is underway. In Phase–II it is planned to exploit full potential of application of AI techniques for intelligent automation of welding processes.

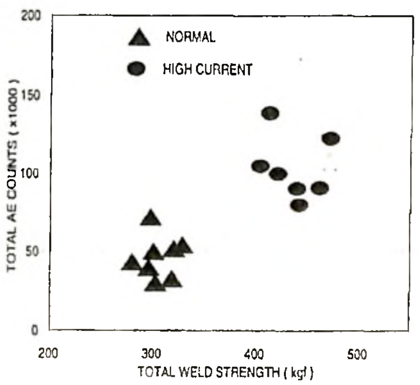

Fig. 9: AE during bearing pad welding

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CROSS WORD

Conceived and constructed : Dr. S. Bhattacharya

a 9				b 10	12	3				c 6					
5				14						2					
11				d 9	14	18	19	1	12	17	1	13	10	12	3
2				6											
e 13	3		f 4	1	11	13	2	8	17					g 3	
2				8						h 7	i 5			16	
j 7	1	12	12	2	6	1		k 7	11	14	20			10	
2				6						9	2	14	2	12	1
3		m 1	11	1	n 3	o 6	12	5	13	1	13			21	
p 10	3				14	5				q 13	1	r 3	10	22	
6					12	14						12			
2		s 4			12	17						10			
5		1			1	16						3			
8		11			8							15			
		t 13	2	9	6	5	12	6	2	5	8				

Clue: Each number represents an alphabet in random order. Replace the number by a suitable alphabet to get a word related to welding. To start with replace 3 by C wherever it appears.

Across			Down		
b(3)	d (9,3)	e (2)	a (14)	c (3)	g (6)
f (7)	j (7)	k (4)	h (5)	i (5)	n (7)
l (4)	m (9)	p (2)	o (5)	r (5)	s (4)
q (5)	t (10)				