



**Review of some artificial intelligence tools for use in
Assembly Automation and some examples of recent
applications**

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Review of some artificial intelligence tools for use in Assembly Automation and some examples of recent applications

Abstract

Purpose (limit 100 words): Seven artificial intelligence tools are reviewed that are useful in Assembly Automation: knowledge-based systems, fuzzy logic, automatic knowledge acquisition, neural networks, genetic algorithms, case-based reasoning and ambient-intelligence.

Design/methodology/approach (limit 100 words): Each artificial intelligence tool is outlined, together with some examples of their use in Assembly Automation.

Findings (limit 100 words): Artificial intelligence has produced a number of useful and powerful tools. This paper reviews some of those tools. Applications of these tools in Assembly Automation have become more widespread due to the power and affordability of present-day computers.

Research limitations/implications (limit 100 words): Many new Assembly Automation applications may emerge and greater use may be made of hybrid tools that combine the strengths of two or more of the tools reviewed in the paper. The tools and methods reviewed in this paper have minimal computation complexity and can be implemented on small assembly lines, single robots or systems with low-capability microcontrollers.

Practical implications (limit 100 words): It may take another decade for engineers to recognize the benefits given the current lack of familiarity and the technical barriers associated with using these tools and it may take a long time for direct digital manufacturing to be considered commonplace... but it is expanding. The appropriate deployment of the new AI tools will contribute to the creation of more competitive Assembly Automation systems.

Social Implications (limit 100 words): Other technological developments in AI that will impact on Assembly Automation include data mining, multi-agent systems and distributed self-organising systems.

Originality/value (limit 100 words): The novel approaches proposed use Ambient Intelligence and the mixing of different AI tools in an effort to use the best of each technology. The concepts are generically applicable across all industrial assembly processes and this research is intended to prove that the concepts work in manufacturing.

1. Introduction

1 Assembly is often of interest as it is one of the last processes within a manufacturing operation. It has
2 traditionally been labour-intensive [1] and can be improved using artificial intelligence (AI). AI emerged
3 as a computer science discipline in the mid 1950s [2,3] and it has produced a number of powerful tools
4 that are useful in Assembly Automation for automatically solving problems that would normally require
5 human intelligence. Seven of these tools are reviewed in this paper: knowledge-based systems, fuzzy
6 logic, inductive learning, neural networks, genetic algorithms, case-based reasoning and ambient-
7 intelligence. Seven of these tools are reviewed in this paper: knowledge-based systems, fuzzy
8 logic, inductive learning, neural networks, genetic algorithms, case-based reasoning and ambient-
9 intelligence.
10 intelligence.

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12 AI systems have been improving [4] and new advances in machine intelligence are creating seamless
13 interactions between people and digital systems. Although the introduction of AI into assembly and
14 manufacturing has been slow, it promises to bring improvements in flexibility, reconfigurability and
15 reliability. New machines are exceeding human performance in increasing numbers of tasks. As they
16 merge with us more intimately and we combine our brain power with computer capacity to deliberate,
17 analyse, deduce, communicate and invent, then we may be on the threshold of a new manufacturing age
18 [5].
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25 AI (or machine intelligence) combines a wide variety of advanced technologies to give machines an
26 ability to learn, adapt, make decisions and display new behaviours [6]. This is achieved using
27 technologies such as neural networks [7], expert systems [8,9], self-organizing maps [10], fuzzy logic [11]
28 and genetic algorithms [12] and that machine intelligence technology has been developed through its
29 application to many areas, for example:
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- 33 • Basic Assembly [13,14].
- 34 • Building modelling [15].
- 35 • Computer vision [16, 17].
- 36 • Environmental engineering [18].
- 37 • Human – computer interaction[19, 20].
- 38 • Internet use [21, 22].
- 39 • Powered assistance [23, 24].
- 40 • Maintenance and inspection [25, 26].
- 41 • Robotic manipulation [27, 28].
- 42 • Robotic programming [29, 30].
- 43 • Sensing [31, 32].
- 44 • Teleoperation [33, 34]

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54 These developments in machine intelligence are being introduced into ever more complex assembly
55 automation and manufacturing systems. At the click of a mouse or the flick of a switch or the thought of
56 a brain... you might have almost anything made and assembled to order.
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59 Some recent examples of this research work are in this general review paper, which also presents some
60 ongoing work at the University of Portsmouth.

2. Knowledge-based systems

1 Knowledge-based (or expert) systems are computer programs embodying knowledge about a domain for
2 solving problems related to that domain [2]. An expert system usually has two main elements, a
3 knowledge base and an inference mechanism. The knowledge base contains domain knowledge which
4 may be expressed as a combination of 'IF-THEN' rules, factual statements, frames, objects, procedures
5 and cases. An inference mechanism manipulates stored knowledge to produce solutions to problems.
6 Knowledge manipulation methods include using inheritance and constraints (in a frame-based or object-
7 oriented expert system), retrieval and adaptation of case examples (in case-based systems) and the
8 application of inference rules (in rule-based systems), according to some control procedure (forward or
9 backward chaining) and search strategy (depth or breadth first).

10 A Rule-Based System describes knowledge of a system in terms of IF...THEN..ELSE. Specific
11 knowledge can be used in order to make decisions. These systems are good at representing knowledge
12 and decisions in a way that is understandable to humans. Due to the rigid rule-base structure they are
13 less good at handling uncertainty and are poor at handling imprecision. A typical rule-based system has
14 four basic components: a list of rules or rule base, which is a specific type of knowledge base; an
15 inference engine [35, 36] or semantic reasoner, which infers information or takes action based on the
16 interaction of input and the rule base; temporary working memory; and a user interface or other
17 connection to the outside world through which input and output signals are received and sent.

18 The concept in Case-Based Reasoning is to adapt solutions from previous problems to current problems.
19 These solutions are stored within a database and can represent the experience of human specialists.
20 When a problem occurs that a system has not experienced, it compares with previous cases and selects
21 one that is closest to the current problem. It then acts upon the solution given and updates the database
22 depending upon the success or failure of the action [37]. Case-Based Reasoning systems are often
23 considered to be an extension of Rule-Based Systems. They are good at representing knowledge in a
24 way that is clear to humans, but they also have the ability to learn from past examples by generating
25 additional new cases. Case-based reasoning has been formalized for purposes of computer reasoning
26 as a four-step process: 1. Retrieve: Given a target problem, retrieve cases from memory that are
27 relevant to solving it. A case consists of a problem, its solution, and, typically, annotations about how the
28 solution was derived. 2. Reuse: Map the solution from the previous case to the target problem. This may
29 involve adapting the solution as needed to fit the new situation. 3. Revise: Having mapped the previous
30 solution to the target situation, test the new solution in the real world (or a simulation) and, if necessary,
31 revise. 4. Retain: After the solution has been successfully adapted to the target problem, store the
32 resulting experience as a new case in memory. Critics argue that it is an approach that accepts
33 anecdotal evidence as its main operating principle. Without statistically relevant data for backing and
34 implicit generalization, there is no guarantee that the generalization is correct. However, all inductive
35 reasoning where data is too scarce for statistical relevance is inherently based on anecdotal evidence.
36 The concept in Case-Based Reasoning (CBR) is to adapt solutions from previous problems to current
37 problems. These solutions are stored within a database and represent the experience of human

specialists. When a problem occurs that a system has not experienced, it compares with previous cases and selects one that is closest to the current problem. It then acts upon the solution given and updates the database depending upon the success or failure of the action. CBR systems are often considered to be an extension of Rule-Based Systems. As with Rule-Based Systems, CBR systems are good at representing knowledge in a way that is clear to humans, however, CBR systems also have the ability to learn from past examples by generating additional new cases. Figure 1 shows a CBR System.

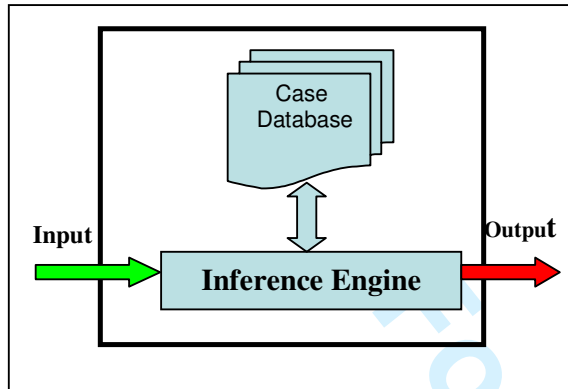


Figure 1 – A Case Based Reasoning System

Many expert systems are developed using programs known as 'shells'; ready-made expert systems complete with inferencing and knowledge storage facilities but without the domain knowledge. Some sophisticated expert systems are constructed with the help of 'development environments'. The latter are more flexible than shells in that they also provide means for users to implement their own inferencing and knowledge representation methods. Some details about expert systems shells and development environments are in Ref [38-40].

Among the six tools considered in this paper, expert systems are probably the most mature, with many commercial shells and development tools available to facilitate their construction. Consequently, once the domain knowledge to be incorporated in an expert system has been extracted, the process of building the system is relatively simple. The ease with which expert systems can be developed has led to a large number of applications of the tool. In Assembly Automation, applications can be found for a variety of tasks including selection of machine elements, tools, equipment and processes, signal interpreting, condition monitoring, fault diagnosis, machine and process control, machine design, process planning, production scheduling and system configuring. Some examples of specific tasks undertaken by expert systems are:

- Automatic programming in robotic assembly [41].
- Assembly sequence planning [42, 43].
- Assembly part design [44].
- Selecting cutting tools and machining strategies [45].
- Identifying and planning inspection schedules [46].
- Configuring paper feeding mechanisms [47].
- Automatic remeshing during a finite-elements analysis [48].

More information on the technology of expert systems is in [3, 49].

1 A disadvantage of ordinary rule-based expert systems is that they cannot handle new situations not
2 covered explicitly in their knowledge bases (that is, situations not fitting exactly those described in the 'IF'
3 parts of the rules). These rule-based systems are unable to produce conclusions when such situations
4 are encountered. They are therefore regarded as shallow systems which fail in a 'brittle' manner, rather
5 than exhibit a gradual reduction in performance when faced with increasingly unfamiliar problems, as
6 human experts would.

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11 The use of fuzzy logic [50] which reflects the qualitative and inexact nature of human reasoning can
12 enable expert systems to be more resilient. With fuzzy logic, the precise value of a variable is replaced
13 by a linguistic description, the meaning of which is represented by a fuzzy set, and inferencing is carried
14 out based on this representation. For example, a production rate of 20 widgets per minute can be
15 replaced by 'normal' as the linguistic description of the variable 'production rate'. A fuzzy set defining the
16 term 'normal production rate' might be:

$$\text{normal production rate} = \begin{matrix} 0.0/\text{below 10 widgets per minute} + 0.5/10\text{--}15 \text{ widgets per minute} + 1.0/15\text{--}25 \text{ widgets per minute} + 0.5/25\text{--}30 \\ \text{widgets per minute} + 0.0/\text{above 30 widgets per minute.} \end{matrix}$$

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28 The values 0.0, 0.5 and 1.0 are the degrees or grades of membership of the production ranges below 10
29 widgets per minute (above 30 widgets per minute.), 10–15 widgets per minute (25–30 widgets per
30 minute), and 15–25 widgets per minute to the given fuzzy set. A grade of membership equal to 1
31 indicates full membership and a null grade of membership corresponds to total non-membership.

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35 Knowledge in an expert system employing fuzzy logic can be expressed as qualitative statements, (or
36 fuzzy rules), such as 'If the room temperature is normal, then set the heat input to normal'. A reasoning
37 procedure known as the compositional rule of inference, which is the equivalent of the modus-ponens
38 rule in rule-based expert systems, enables conclusions to be drawn by generalisation (extrapolation or
39 interpolation) from the qualitative information stored in the knowledge base. For instance, when the
40 production rate is detected to be 'slightly below normal', a controlling fuzzy expert system might deduce
41 that the inputs should be set to 'slightly above normal'. Noting that this conclusion might not have been
42 contained in any of the fuzzy rules stored in the system.

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48 Fuzzy Expert Systems (FES) use fuzzy logic to handle the uncertainties generated by incomplete or
49 partially corrupt data. The technique uses the mathematical theory of fuzzy sets to simulate human
50 reasoning. Humans can easily deal with ambiguity (areas of grey) in terms of decision making, yet
51 machines find it difficult [51].

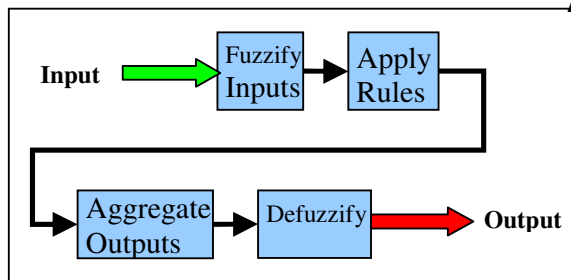


Figure 2 – A Fuzzy Logic Controller

Figure 2 shows an architecture for a fuzzy logic based controller.

Fuzzy logic has many applications in Assembly Automation where the domain knowledge can be imprecise. Fuzzy Logic is well suited where imprecision is inherent due to imprecise limits between structures or objects, limited resolution, numerical reconstruction methods and image filtering. For example, applications in structural object recognition and scene interpretation have been developed using Fuzzy Sets within expert systems. Fuzzy expert systems are suitable for applications that require an ability to handle uncertain and imprecise situations. They do not have the ability to learn as the values within the system are preset and cannot be changed. Further information on fuzzy logic and fuzzy sets can be found in Ref. [52, 53, 54].

Notable successes have been achieved in the area of process and machine control:

- Monitoring and controlling welding processes [28, 55].
- Robotic folding of fabrics [56].
- Prediction of sensory properties [57].
- Robot control [58].
- Supply chain management [59].

Further information on fuzzy logic and fuzzy sets in manufacturing can be found in Ref. [60].

4. Automatic knowledge acquisition

Getting domain knowledge to build into a knowledge base can be complicated and time consuming. It can be a bottleneck in constructing an expert system. Automatic knowledge acquisition techniques were developed to address this, for example in the form of IF–THEN rules (or an equivalent decision tree). This sort of learning program usually requires a set of examples as a learning input. Each example is characterised by the values of a number of attributes and the class to which it belongs.

One approach for example is through a process of 'dividing-and-conquering', where attributes are selected according to some strategy (for example, to maximise the information gain) to divide the original example set into subsets, the inductive learning program builds a decision tree that correctly classifies the given example set. The tree represents the knowledge generalised from the specific examples in the set. This can subsequently be used to handle situations not explicitly covered by the example set.

In another approach known as the 'covering approach', the inductive learning program attempts to find groups of attributes uniquely shared by examples in given classes and forms rules with the IF part as conjunctions of those attributes and the THEN part as the classes. The program removes correctly classified examples from consideration and stops when rules have been formed to classify all examples in the given set [2].

Another approach is to use logic programming instead of propositional logic to describe examples and represent new concepts. That approach employs the more powerful predicate logic to represent training examples and background knowledge and to express new concepts. Predicate logic permits the use of different forms of training examples and background knowledge. It enables the results of the induction process, that is the induced concepts, to be described as general first-order clauses with variables and not just as zero-order propositional clauses made up of attribute-value pairs. There are two main types of these systems, the first, based on the top-down generalisation/specialisation method, and the second, on the principle of inverse resolution [36].

A number of learning programs have been developed, for example: ID3 [61], which is a divide-and-conquer program, the AQ program [35], which follows the covering approach, the FOIL program [36], which is an ILP system adopting the generalisation/specialisation method, and the GOLEM program [36], which is an ILP system based on inverse resolution. Although most programs only generate crisp decision rules, algorithms have also been developed to produce fuzzy rules [62].

Due to its requirement for a set of examples in a rigid format (with known attributes and of known classes), automatic learning has been tricky to use in Assembly Automation, as not many assembly automation problems can be described easily in terms of such a set of examples. This sort of learning is generally more suitable for problems where attributes have discrete or symbolic values rather than those with continuous-valued attributes as in many assembly automation problems. More information is in [63, 64, 65].

Some examples of applications of inductive learning are:

- Controlling a laser cutting robot [66];
- Classifying complex and noisy patterns [67];
- Analysing constructability [68].

5. Neural networks

Neural networks can also capture domain knowledge from examples. However, they do not archive the acquired knowledge in an explicit form such as rules or decision trees and they can readily handle both continuous and discrete data. They also have a good generalisation capability as with fuzzy expert systems.

A neural network is a computational model of the brain. Neural network models usually assume that computation is distributed over several simple units called neurons, which are interconnected and

operate in parallel (hence, neural networks are also called parallel-distributed-processing systems or connectionist systems).

The most popular neural network is the multi-layer perceptron, which is a feedforward network: all signals flow in a single direction from the input to the output of the network. Feedforward networks can perform static mapping between an input space and an output space: the output at a given instant is a function only of the input at that instant. Recurrent networks, where the outputs of some neurons are fed back to the same neurons or to neurons in layers before them, are said to have a dynamic memory: the output of such networks at a given instant reflects the current input as well as previous inputs and outputs.

Implicit 'knowledge' is built into a neural network by training it. Some neural networks can be trained by being presented with typical input patterns and the corresponding expected output patterns. The error between the actual and expected outputs is used to modify the strengths, or weights, of the connections between the neurons. This method of training is known as supervised training. In a multi-layer perceptron, the back-propagation algorithm for supervised training is often adopted to propagate the error from the output neurons and compute the weight modifications for the neurons in the hidden layers.

Some neural networks are trained in an unsupervised mode, where only the input patterns are provided during training and the networks learn automatically to cluster them in groups with similar features. For more information on neural networks, see Ref. [69, 70, 71].

Artificial Neural Networks typically have inputs and outputs, with processing within hidden layers in between. Inputs are independent variables and outputs are dependent. ANNs are flexible mathematical functions with configurable internal parameters. To accurately represent complicated relationships, these parameters are adjusted through a learning algorithm. In 'supervised' learning, examples of inputs and corresponding desired outputs are simultaneously presented to networks, which iteratively self-adjust to accurately represent as many examples as possible. Once trained then ANNs can accept new inputs and attempt to predict accurate outputs. To produce an output, the network simply performs function evaluation. The only assumption is that there exists some continuous functional relationship between input and output data. Neural networks can be employed as mapping devices, pattern classifiers or pattern completers (auto-associative content addressable memories and pattern associators). Like expert systems, they have found a wide spectrum of applications in almost all areas of Assembly Automation, addressing problems ranging from modelling, prediction, control, classification and pattern recognition, to data association, clustering, signal processing and optimisation. Some recent examples of such applications are:

- Estimating printed circuit board assembly times [72].
- Compensating for nonlinearities [73].
- Inspection of Soldering Joints [74].
- Automated failure classification for assembly with self-tapping threaded fastenings [75].
- Tele-operation [76].
- Optimizing spot welding parameters in a sheet metal assembly [77].
- Controlling a flexible assembly operation [30].

- Analysing vibration spectra [78].

6. Genetic algorithms

A genetic algorithm is a stochastic optimisation procedure inspired by natural evolution [2]. A genetic algorithm can yield the global optimum solution in a complex multi-modal search space without requiring specific knowledge about the problem to be solved. However, for a genetic algorithm to be applicable, potential solutions to a given problem must be representable as strings of numbers (usually binary) known as chromosomes and there must be a means of determining the goodness, or fitness, of each chromosome. A genetic algorithm operates on a group or population of chromosomes at a time, iteratively applying genetically based operators such as cross-over and mutation to produce fitter populations containing better solution chromosomes. The algorithm normally starts by creating an initial population of chromosomes using a random number generator. It then evaluates each chromosome. The fitness values of the chromosomes are used in the selection of chromosomes for subsequent operations. After the cross-over and mutation operations, a new population is obtained and the cycle is repeated with the evaluation of that population. For further information on genetic algorithms, see Refs. [79, 80, 81].

Genetic algorithms have found applications in Assembly Automation problems involving complex combinatorial or multi-parameter optimisation. Some recent examples of those applications are:

- Efficiency in batch selective assembly [82].
- Car assembly line fault diagnosis [83].
- Job-shop scheduling [84].
- Assembly line balancing [85].
- Robot Path Planning [86].

7. Ambient-intelligence.

Ambient Intelligence has been promoted for the last decade as a vision of people working easily in digitally controlled assembly environments in which the electronics can anticipate their behaviour and respond to their presence. The concept of Ambient Intelligence is for seamless interaction between people and digital systems to meet actual and anticipated needs.

Use in industry has been limited but new more intelligent and more interactive systems are at the research stage. From the perspective of assembly automation, a less human and more system-centred definition of Ambient Intelligence needs to be considered. Modern manufacturing concepts tend to be human-centred approaches so that the application of Ambient Intelligence technologies in a combination with Knowledge Management may be a promising approach. Many research issues still have to be resolved in order to bring the Ambient Intelligence technology to industrial sectors, such as robust, reliable (wireless) sensors and context-sensitivity, intelligent user interfaces, safety, security and so forth.

Ambient Intelligence information and knowledge gathered within a manufacturing environment represents an untapped resource for optimisation of energy use of industrial installations and processes

and for possibilities to provide energy efficiency services for manufacturing. The introduction of Ambient Intelligence technologies is still in an initial phase. However, it is promising to bring advantages in flexibility, reconfigurability and reliability. At the same time, prices of sensors and tags are reducing. Development and implementation of new manufacturing concepts based on Ambient Intelligence systems in the mid and long-term are likely. A large number of industrial companies will probably introduce different Ambient Intelligence technologies onto the shop-floor.

On the other hand, manufacturing technology vendors will need to equip their machines, robots, tools with additional Ambient Intelligence features and utilise the advantages of Ambient Intelligence integrated within the shop-floor environment to provide new functionalities (for example: self-configuration, context-sensitivity etc.) and improve performances of their products.

More information is in [87, 88].



8. Some artificial intelligence applications at the University of Portsmouth

This section briefly reviews some applications of the aforementioned artificial intelligence tools at the University of Portsmouth that are assisting industry in the adoption of artificial intelligence in assembly and manufacturing.

8.1 Control of assembly robots. Simple rules have been investigated that modify pre-planned paths and improve gross robot motions associated with pick & place assembly tasks [89] and rules to predict terrain contours are being developed using a feed-forward neural network [90]. Robots at Ford Motor Company what were used to demonstrate the systems are shown in figure 3. Case-based reasoning to reuse robot programs (or parts of programs) to automatically program assembly tasks. The combined work is already showing that robot teaching time can be reduced and automatic programming and re-programming may help to introduce robots into smaller and medium enterprises. Other projects are using simple expert systems are being used to improve tele-operation [91, 92, 93].

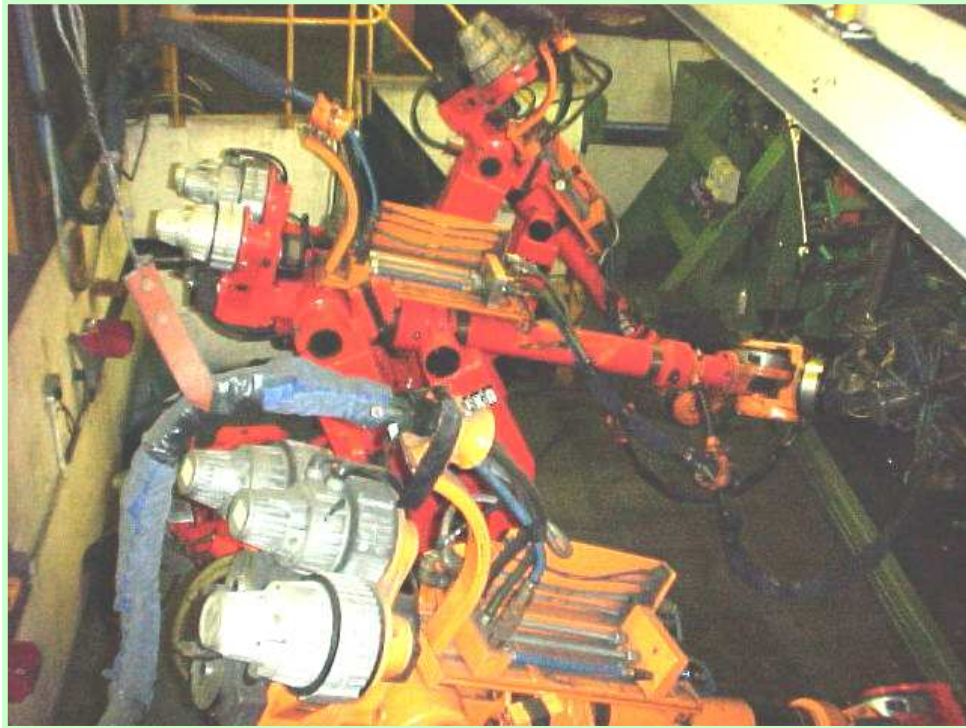


Figure 3: Robots at Ford Motor Company what were used to demonstrate the systems

8.2. Process control. An expert system is being developed to assist in process control and to enhance the implementation of statistical process control. A bespoke expert system uses a hybrid rule-based and pseudo object-oriented method of representing standard statistical process control knowledge and process-specific diagnostic knowledge. The amount of knowledge involved can be large, which justifies the use of a knowledge-based systems approach. The system is being enhanced by integrating a neural network module with the expert system modules to detect any abnormal patterns.

8.3. Automatic product design for assembly. Two major projects have investigated automatic design-for-assembly. The systems provide designers with suggestions for improvement. A first multi-expert system analyses a design and provides designers with ideas for changes to designs at an early stage in order to improve assembly later in the manufacturing process. A second system improves the design of High Recirculation Airlift Reactors.

- The first system consists of four expert systems: Computer Aided Design (CAD) Expert, Automated Assembly Expert, Manual Assembly Expert and Design Analysis Expert. The Design Analysis Expert includes a sub-system to collate the information from the Assembly Experts and to provide costs and advice [94]. The approach and the systems can reduce manufacturing costs and lead times. A

knowledge-based reckoning approach to design-for-assembly automation has been used. The system can estimate assembly-time and cost for manual or automatic assembly and select suitable assembly techniques.

- A second system has been created that could replace a main ICI design program called aprpc which has been the industrial standard program for large scale High Recirculation Airlift Reactors (a process to produce clean water) [8, 18, 95]. When a new reactor is designed, calculations are performed using input data that specify the design criteria in terms of process performance, geometry, kinetic factors and dynamic performance factors. From this specification, the new design program calculates the construct of the product. A high recirculation airlift reactor is shown in figure 4.

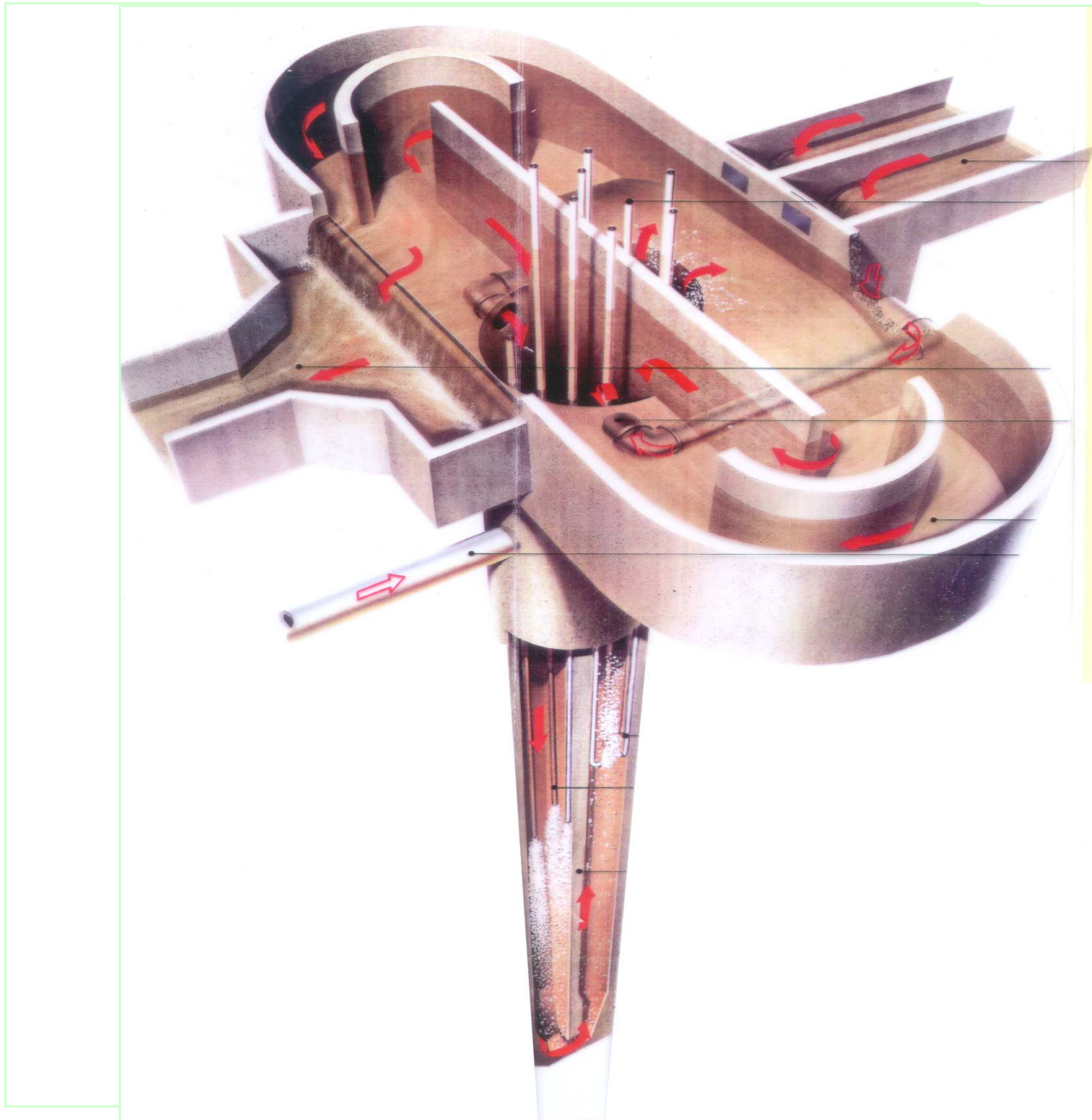


Figure 4: A high recirculation airlift reactor.

8.4. Fuzzy control. A robotic welding system is being created that uses image processing techniques and a CAD model to provide information to a multi-intelligent decision module [96]. The system uses a combination of techniques to suggest weld requirements. These suggestions are evaluated, decisions are made and then weld parameters are sent to a program generator. The status of welding process is difficult to monitor because of the intense disturbance during the process. Other work is using multiple sensors to obtain information about the process. Fuzzy measurement and fuzzy integral methods are being investigated to fuse extracted signal features in order to predict the penetration status of the welding process.

8.5. Neural-network-based product inspection. Two projects are using neural networks for product inspection, one is recognizing shipbuilding parts and a second is using cameras to detect and classify defects. Neural networks are useful for these types of application because of the common difficulty in precisely describing various types of defects and differences. The neural networks are able to learn the classification task automatically from examples.

- The first system is managing to recognise shipbuilding parts using artificial neural networks and Fourier descriptors [17]. Improvements have been made to a pattern recognition system for recognising shipbuilding parts [26]. This has been achieved by using a new simple and accurate corner-finder. The new system initially finds corners in an edge detected image of a part and uses that new information to extract Fourier descriptors to feed into a neural network to make decisions about shapes. Using an all-or-nothing accuracy measure, the new systems have achieved an improvement over other systems.

- A second intelligent inspection system has been built that consists of cameras connected to a computer that implements neural-network-based algorithms for detecting and classifying defects. Outputs from the network indicate the type of defect. Initial investigation suggests that the accuracy of defect classification is good (in excess of 85%) and faster than manual inspection. The system is also used to detect defective parts with a high accuracy (almost 100%).

8.6. Genetic Algorithms to create an ergonomic workplace layout. A Genetic Algorithm for deciding where to place equipment in a work cell is being developed. The layout produced by the programme will be such that the most frequently needed equipment is most easily reached. A Genetic Algorithm is suitable for this optimisation problem because it can readily accommodate multiple constraints expressing the principles of good ergonomic layout.

8.7 Ambient Intelligence to improve energy efficiency. Ambient Intelligence and Knowledge Management technologies are being used to optimise the energy efficiency of manufacturing units [88]. This benefits both the company and the environment as the carbon footprint is reduced. Different measuring systems are being applied to monitor energy use [97]. Ambient data provide the opportunity

to have detailed information on the performance of a manufacturing unit [98]. Knowledge Management facilitates process this information and advise on actions to minimise energy usage but maintain production. Existing energy consumption data from standard measurements is being complemented by Ambient Intelligence related measurements (from interactions of human operators and machines/processes and smart tags) as well as process related measurements (manufacturing line temperatures, line pressure, production rate) and knowledge gathered within the manufacturing assembly unit. This is fed to a Service Oriented Architecture system. Figure 5 shows an experimental system that is being developed to put the methodology to the test.

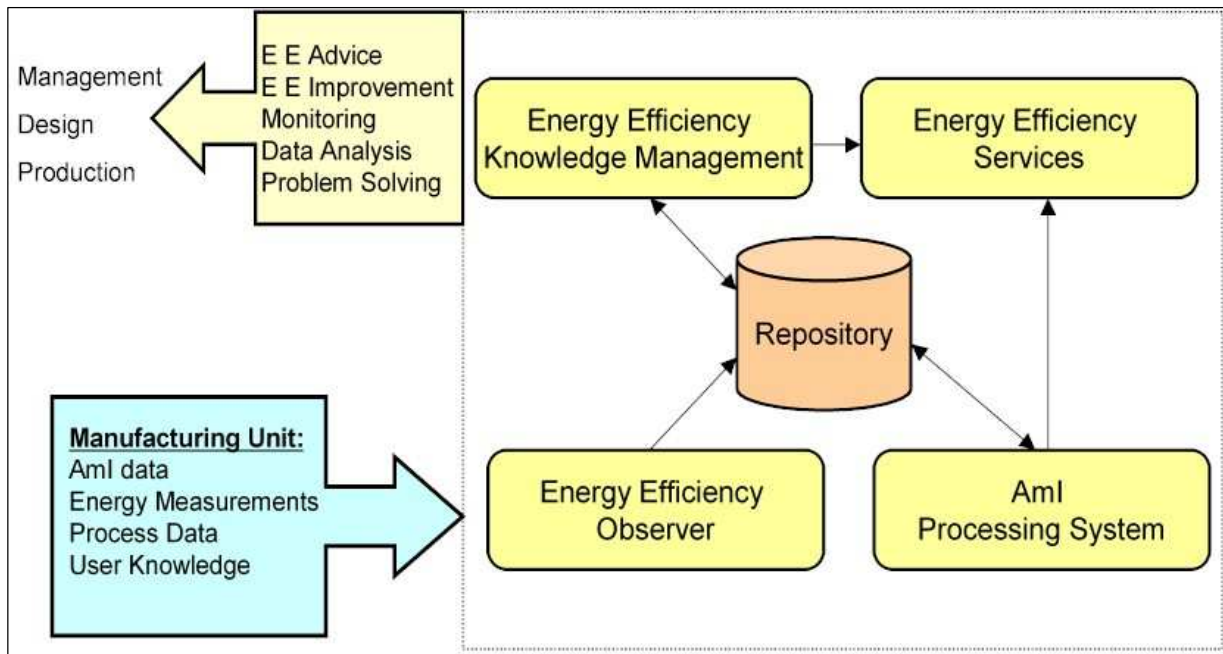


Figure 5: Experimental system to use ambient intelligence to improve energy efficiency

9. Combining different systems

The purpose of a hybrid system is to combine the desirable elements of different AI techniques into one system. The many different methods of implementing AI each have their own strengths and weaknesses. Some effort has been made in combining different methods to produce hybrid techniques with more strengths and less weaknesses. An example is the Neuro-Fuzzy system which seeks to combine the uncertainty handling of Fuzzy Systems with the learning strength of Artificial Neural Networks.

A solution to the problems associated with weld programming is being addressed in this way [96]. An existing system is shown in Figure 6. The system consists of two software systems working in series to construct viable robot programs. The first system, the CAD model interpreter, accepts a CAD model and determines the welds required. This data is fed to the Program Generator which re-orientates the weld requirements in line with the actual real-world orientation of the panel. The program generator then

sends any programs sequentially to the robot (normally one program per weld line). Additional software systems could be incorporated into the existing system at the point where the robot programs are sent to the Robot System. This is because the transmission protocol at this point is standard TCP/IP and any programs to be sent can be viewed as text files.

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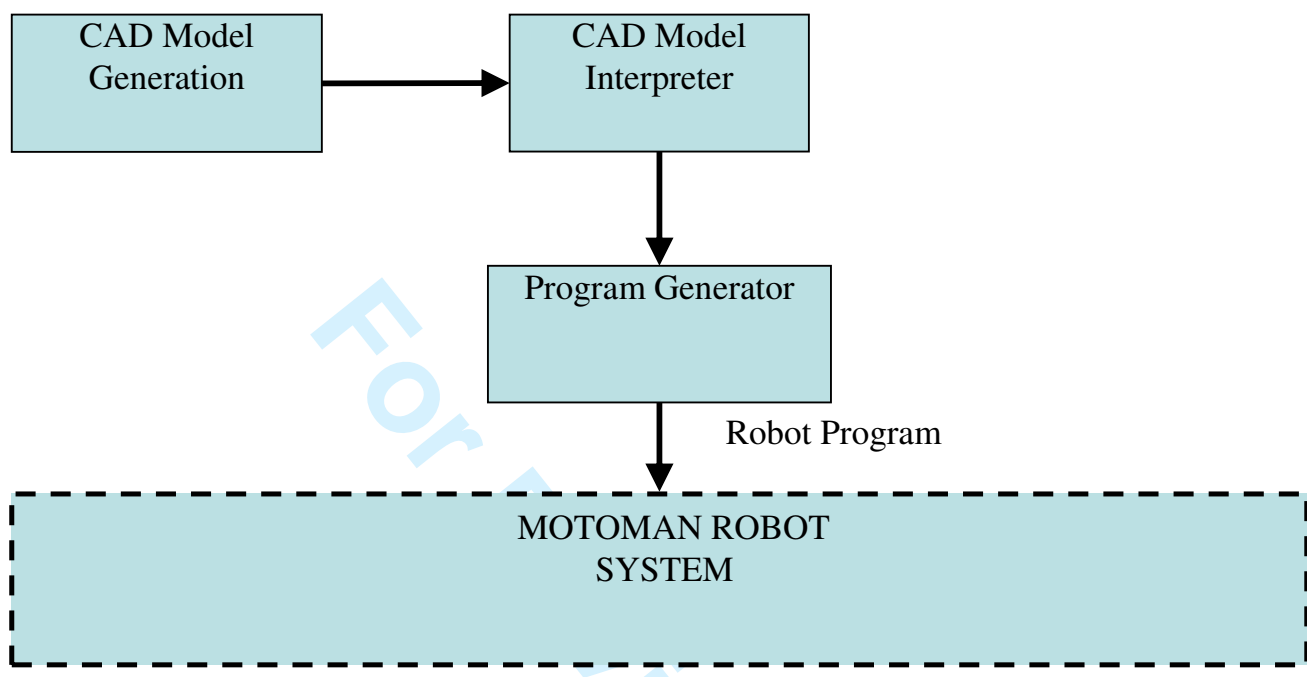


Figure 6 – Existing RinasWeld / Motoman System

A new proposed system (shown in Figure 7) will gather that data from an image. The visual data and CAD model data will be used in conjunction to determine an object list, that object list will be passed to a weld identifier module that will use AI techniques to determine weld requirement.

The proposed system uses a combination of AI techniques working in parallel to suggest weld requirements. These suggestions are then evaluated and decisions made regarding the weld required. These parameters are then sent to a new program generator, which produces a custom robot program for use on the shop floor. Image capture methods are being combined with a decision making system that uses multiple AI techniques to decide on weld requirements for a job.

The system will combine Real-world visual data with data provided by the CAD model. It will then use this combined data to present differing AI systems with the same information. These systems will then make weld requirement suggestions to a Weld Identifier module (figure 8). This module will evaluate the suggestions and determine the optimum weld path. The suggestions will then be passed to the existing robot program generator.

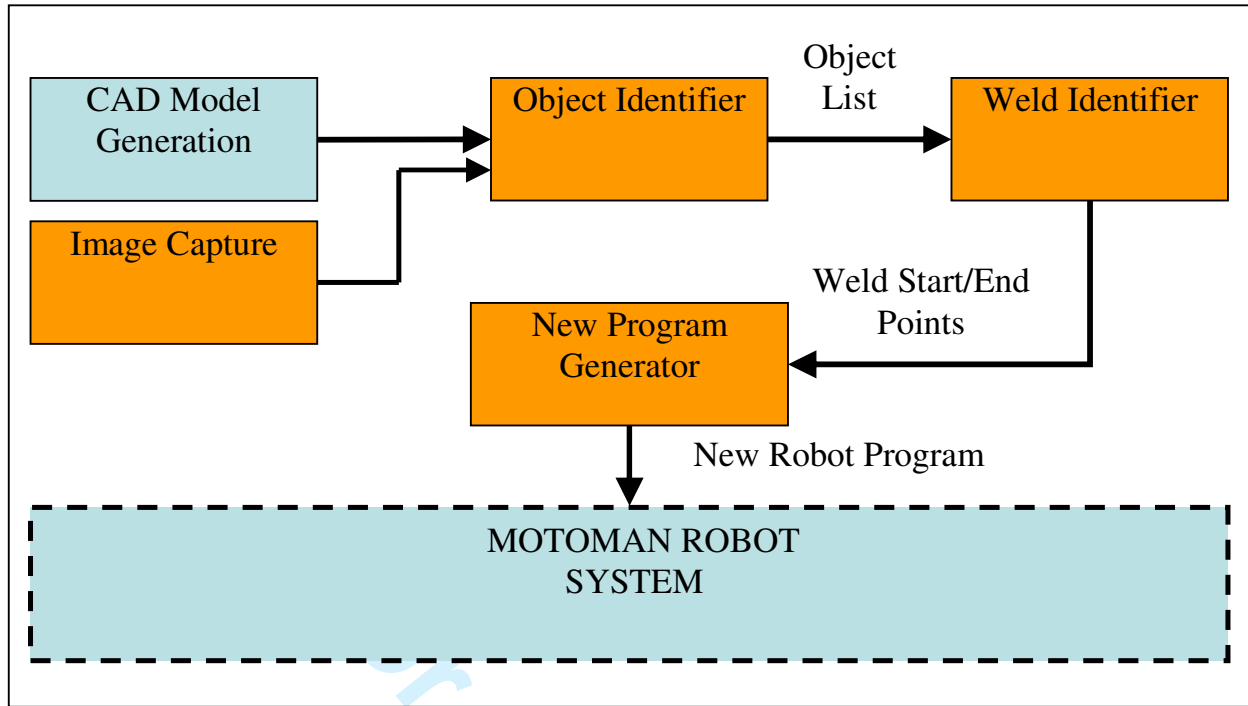


Figure 7 – Proposed System Flow Diagram

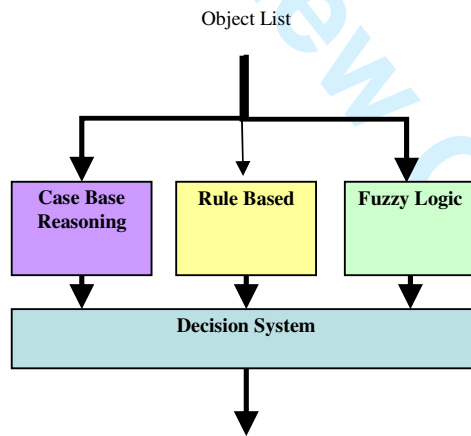


Figure 8 – Weld Identifier Module

The current state of this research is that the robot program generation systems have been created and tested and used to produce consistent straight line welds. A simple edge detection system has been created. Work surrounding the AI systems is in the early stages and will be taken further over the next six months. During this time the multi-intelligent decision module framework will be further developed and combinations of AI techniques tested. The AI techniques to be tested will include Rule-based, Case-based and Fuzzy systems. Any created system needs to be able to handle the uncertainty of

unidentified objects within the image; however, when all objects are positively identified there should be little doubt as to the weld path.

Another example of combining different artificial intelligence tools is the Fuzzy Network [97]. The nodes of this type of network are fuzzy rule bases and the connections between the nodes are interactions in the form of outputs from nodes that are fed as inputs to the same or other nodes. The fuzzy network is a hybrid tool combining fuzzy systems and neural networks due to its underlying grid structure with horizontal levels and vertical layers. This tool is quite suitable for modelling the assembly automation process because the separate assembly stages can be described as modular fuzzy rule bases interacting in sequential/parallel fashion and feed forward/ feedback context. The main advantages from the application of this hybrid modelling tool are better accuracy due to the single fuzzification-inference-defuzzification and higher transparency due to the modular approach used. These advantages are quite crucial bearing in mind the uncertainties in the data and the interconnected structure of the assembly automation process.

10. Discussion

This all brings us to a point in history when our human biology appears too frail, slow and over-complicated in many industrial situations [6]. To overcome this, we are beginning to mix sensor systems [98] and some powerful new technologies to overcome those weaknesses, and the longer we use that technology, the more we are getting out of it [5]. We use less energy, space, and time, but get more and more assembly output for less cost. The time may be coming when a human being will be able to think of an object and then watch it appear before their eyes [5, 99]. For example, rapid-prototyping is already automatically constructing physical objects using solid freeform fabrication and proving to have advantages over high speed machining for manufacturing prototypes. In the Regional Centre for Manufacturing Industry at Portsmouth University, machines read in data from drawings and lay-down successive layers to build up a model from a series of cross sections. This additive fabrication is able to create almost any shape by manufacturing solid objects through the sequential delivery of energy and material to specified points in space to produce a part. Rapid-prototyping is slowly including rapid-manufacturing and assembly and rapid-prototyping techniques are already being used for manufacture, albeit in small numbers. The new machines are exceeding human performance in increasing numbers of tasks. As they merge with us more intimately and we combine our brain power with computer capacity to deliberate, analyse, deduce, communicate and invent, then we may be on the threshold of a new manufacturing and assembly age. Developments in machine intelligence are being introduced into rapid-prototyping, rapid manufacture and rapid assembly as globalization and out-sourcing change the structure of manufacturing, design and assembly processes. They are becoming distributed, both organizationally and geographically. Competition is increasing and companies are faced with high rates of technological change, shrinking product life cycles, and intense competition in global, dynamic, and

fragmented markets. AI is becoming important in reducing costs and time. Designs can be evaluated using a prototype made and assembled in hours or days instead of weeks. Design flaws can be detected and corrected more quickly and new products can be tested and retested much faster. AI in assembly can increase effective communication, reduce mistakes, minimize engineering changes and extend product lifetime by adding necessary features and eliminating redundant features early. Development time therefore reduces. By allowing engineering, manufacturing, marketing, and purchasing to examine a product early in the design process, mistakes can be corrected and changes made while they are easy and inexpensive.

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10. Conclusion

1 Over the past 40 years, artificial intelligence has produced a number of powerful tools. This paper has
2 reviewed some of those tools: knowledge-based systems, fuzzy logic, automatic learning, neural
3 networks, ambient intelligence and genetic algorithms. Applications of these tools in Assembly
4 Automation have become more widespread due to the power and affordability of present-day computers.
5 Many new Assembly Automation applications may emerge and greater use may be made of hybrid tools
6 that combine the strengths of two or more of the tools reviewed here. Other technological developments
7 in AI that will impact on Assembly Automation include data mining, multi-agent systems and distributed
8 self-organising systems. The appropriate deployment of the new AI tools will contribute to the creation of
9 more competitive Assembly Automation systems.
10

11 It may take another decade for engineers to recognize the benefits given the current lack of familiarity
12 and the technical barriers associated with using these tools and it may take a long time for direct digital
13 manufacturing to be considered commonplace... but it is expanding.
14

15 The tools and methods reviewed in this paper have minimal computation complexity and can be
16 implemented on small assembly lines, single robots or systems with low-capability microcontrollers.
17

18 The novel approaches proposed use Ambient Intelligence and the mixing of different AI tools in an effort
19 to use the best of each technology. The concepts are generically applicable across all industrial
20 assembly processes and this research is intended to prove that the concepts work in manufacturing.
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