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PII: S0954-1810(97)00024-1

Artificial Intelligence in Engineering **12** (1998) 253–260

0954-1810/98/$19.00

Fuzzy logic in a blackboard system for controlling plasma deposition processes

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(Received 8 January 1997; revised version received 7 April 1997; accepted 22 May 1997)

A blackboard system, ARBS, has been used to control a plasma processing unit, which is used for depositing coatings on the surface of electronic or mechanical components. Previous applications of ARBS have been based on crisp logic, but fuzzy logic was added in this study for plasma deposition control. Fuzzy rules have been introduced into ARBS without changing either the rule syntax or the existing inference engines, thereby demonstrating the flexibility of the software. Consequently crisp and fuzzy rules can coexist within a single knowledge source (i.e. module).

An efficient technique for defuzzification has been employed in which the membership functions are replaced by Dirac delta functions. The technique is equivalent to standard methods of defuzzification, without loss of precision or accuracy, but with a reduced number of calculations. Multi-variable control of DC-bias (an electrical parameter) by automatic adjustment of pressure and RF (radio frequency) electrical power is demonstrated. © 1998 Elsevier Science Limited. All rights reserved.

Key words: ARBS, blackboard system, defuzzification, fuzzy logic, multi-variable control, plasma processing, rules.

1 INTRODUCTION

A plasma is an ionised gas (Fig. 1). By suitable adjustment of parameters, ions and neutral species (i.e. atoms, uncharged molecules and uncharged molecular fragments) from the plasma can be made to strike the surface of a specimen in a controlled manner. This technique, called plasma processing, is widely used for modifying material surfaces by deposition of coatings or by etching of masked regions.[1] It is of particular importance in the microelectronics industry. The current work concerns deposition processes only, specifically the deposition of diamond-like carbon, which combines high thermal conductivity with good electrical insulation. The quality and reproducibility of these processes rely strongly on the plasma parameters. The directly adjustable parameters are pressure, substrate temperature, gas composition, gas flow rate, RF (radio frequency) electrical power and process time.

The conditions within the plasma determine the nature of the material deposited. These conditions are represented by a set of intermediate variables which are dependent on the adjustable parameters but are not directly controllable themselves. The intermediate variables include energies and fluxes of ions, neutral species and electrons. They also include electrical properties such as the so-called DC-bias voltage that is associated with RF excited low- pressure plasma systems. This voltage arises as a consequence of rectification of the applied RF voltage by the non-linear load presented by the ionised gas plasma. It has particular significance since it is closely related to the energy of ions arriving at surfaces. Furthermore, it is a readily measurable parameter and it is therefore well-suited to experiments in parameter control.

The relationships between the variables are difficult to model as they are interdependent and can be non-linear. The problem is compounded by the difficulty in transferring successful operating conditions from one set of equipment to another, and in scaling up a process. Traditional control methods, which rely on a well-defined model of the process, are therefore ill-suited to the control of plasma variables. Fuzzy logic, on the other hand, can circumvent some of these difficulties by making use of expert knowledge from human operators.

Control of a plasma unit requires both the interpretation of diagnostic data (often in graphical form) and on-line decision-making. This paper reports on the implementation

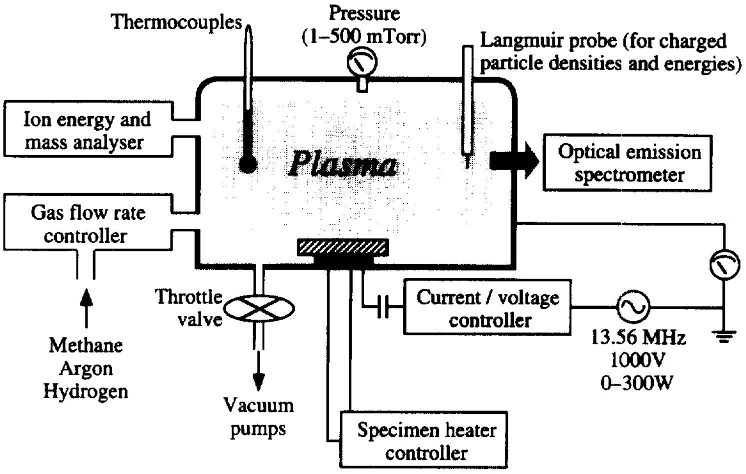


Fig. 1. Plasma deposition of diamond-like carbon.

of fuzzy logic into ARBS (Algorithmic and Rule-based Blackboard System) and the effectiveness of this system as a plasma controller. ARBS is an 'in-house' software package which has previously been applied to the automated interpretation of ultrasonic images[2] and management of a telecommunications network.[3]

2 THE BLACKBOARD MODEL OF ARBS

ARBS is based on the blackboard model of problem-solving.[4,5] Knowledge is divided into modules, called knowledge sources (KSs), as shown in Fig. 2. At run-time, a model of the problem and its solution evolves in a global memory area, i.e. the blackboard. The knowledge sources can read information from the blackboard, add new information to the blackboard and delete old information. Thus the blackboard is the medium through which KSs communicate and co-operate. The blackboard is divided into panels corresponding to different levels of analysis of the problem from low-level data through to high-level inferences. ARBS has been implemented in the Pop-11 language, within the Poplog environment.

ARBS currently has provisions for five different types of knowledge source. The first three types are all rule-based, but with different inference mechanisms. The remaining two types are for procedures or functions, and for neural networks. Rules in ARBS also have direct access to procedures and functions, thereby allowing rule-based and procedural programming styles to be used within a single rule-based knowledge source. Each rule-based knowledge source is accompanied by a rule dependence network, which is generated automatically. The dependence network is used by the inference engines to cut down on the number of rules considered at any instant, thereby improving efficiency. ARBS dependence networks are distinct from Rete networks;[6] their use is described in more detail elsewhere.[3,4]

Each KS is contained in a record (Fig. 3), where one of the fields stores the KS type, Each KS has a set of preconditions, which must be satisfied before it can be activated. There is also an activation flag, which allows individual KSs to be switched on or off. For rule-based KSs there are also fields containing the rules, their dependence network and the selected inference engine. Before a KS is deactivated, any actions in the *actions* field are performed. For purely procedural KSs, the procedures or functions are simply referenced in the *actions* field.

One procedural KS and six rule-based KSs control the plasma deposition process, and each KS is dedicated to a specific task:

input of deposition parameters – procedural KS
control of vacuum pump – down
heater operation
starting the plasma
monitoring the deposition process
fuzzy logic control
shutting down the system
} rule – based KSs.

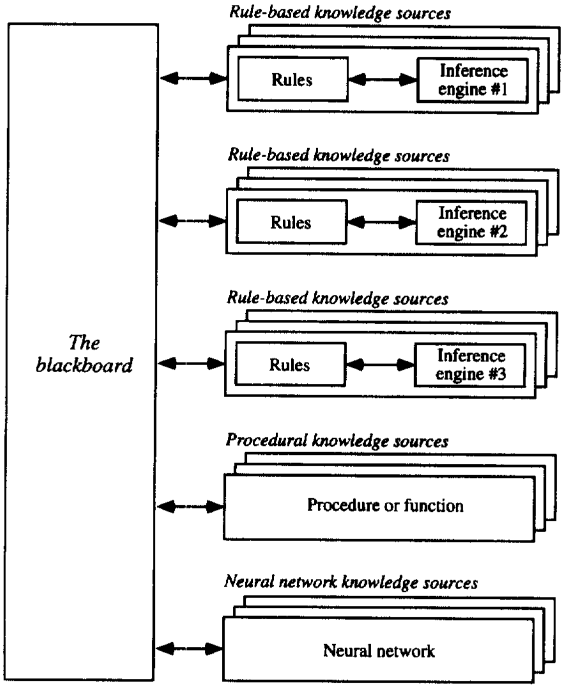


Fig. 2. The blackboard architecture of ARBS.

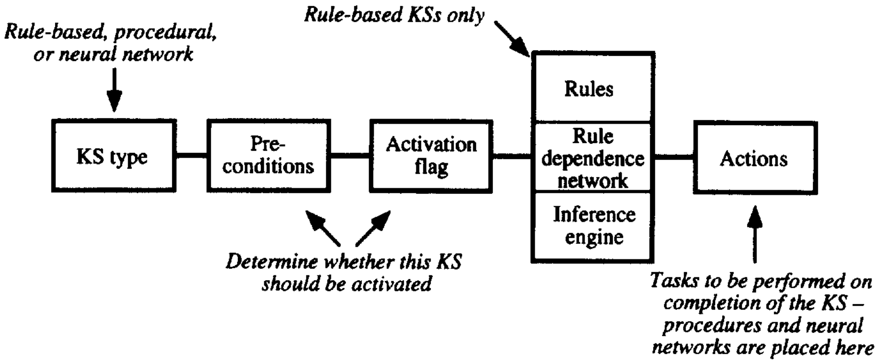


Fig. 3. Structure of an ARBS knowledge source.

3 RULE STRUCTURE

ARBS rules are used for looking up information on the blackboard, making deductions about information on the blackboard, and posting new information onto the blackboard. Although this is a fairly simple philosophy, it provides a flexible and powerful rule structure in which complex conditions and conclusions can be constructed. External procedures or functions can be accessed directly from within the condition or conclusion parts of any rules.

ARBS rules are comprised of lists, which are interpreted using a pattern-matcher to break them down into their component parts. These components are then evaluated or performed as appropriate. The rules are of the general form

[*rule_number* [*condition*] *implies* [*conclusion or action*]]

where the condition may comprise sub-conditions joined with Boolean operators AND or OR, and the conclusion/action can contain any number of statements.

The condition (or its sub-conditions) can be evaluated in any of the following ways:

- test for, and look up, information on the blackboard;
- run procedures or functions, which may return numerical or Boolean results;
- numerical comparison of variables, constants, or function results.

The conclusion part can comprise any number of the following actions:

- add a conclusion (or other information) to the blackboard;
- remove information from the blackboard;
- run procedures or functions, optionally adding the results to the blackboard;
- report conclusions or actions to the user.

Extensive use is made of local variables, thereby simplifying the flow of information between different parts of the same rule. In contrast, rule-to-rule communication is carried out via the blackboard. Further details of the ARBS rule syntax are given elsewhere.[4]

4 FUZZY RULES

The condition and conclusion parts of fuzzy rules have been implemented as ARBS sub-conditions and sub-conclusions respectively. This has enabled fuzzy rules in ARBS to have the same structure as other rules. They can therefore coexist in a knowledge source and be processed by the same inference engines.

The fuzzy sets used in this application of ARBS are triangular. They can be described by three variables: the number of sets, an upper value, and a lower value (Fig. 4). For each fuzzy variable, this information is stored on the blackboard. Suitable upper and lower values are determined by expert judgement. The upper and lower values are not limits on the fuzzy variables; if a fuzzy variable has a value outside the upper–lower range it will have a membership (μ) of 1 for 'LOW' or for 'HIGH'. Boolean combinations have been implemented using the standard methods:[7]

$$\mu(x\text{AND}y) = \min[\mu(x), \mu(y)]$$

$$\mu(x\text{OR}y) = \max[\mu(x), \mu(y)]$$

$$\mu(\text{NOT}x) = [1 - \mu(x)].$$

One of the goals of the fuzzy controller is to keep the DC-bias at a set point (e.g. −400 volts). DC-bias is an intermediate variable, i.e. one that cannot be controlled directly. It is, however, influenced by changes in pressure and RF

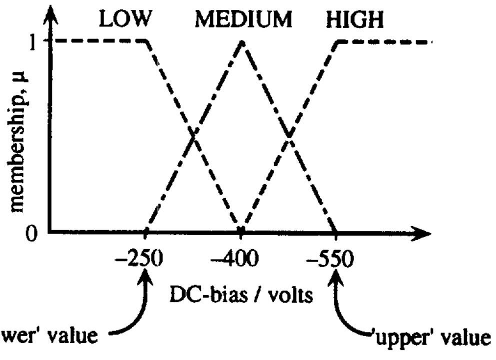


Fig. 4. Triangular fuzzy sets as used in ARBS (three sets in this case).

power, both of which are directly controllable. Three approaches to controlling DC-bias have been demonstrated in ARBS: by adjusting the RF power, by adjusting the pressure, and by adjusting both parameters simultaneously. The corresponding fuzzy rules can be written informally as follows (as DC-bias is negative, 'HIGH' is interpreted as 'more negative' than the nominal setting):

Adjusting RF power only:

if DC-bias is LOW and pressure is HIGH then LARGE INCREASE in RF power
if DC-bias is LOW and pressure is NOT HIGH then INCREASE the RF power
if DC-bias is MEDIUM then DON'T CHANGE the RF power
if DC-bias is HIGH and pressure is NOT LOW then DECREASE the RF power
if DC-bias is HIGH and pressure is LOW then LARGE DECREASE in RF power.

Adjusting pressure only:

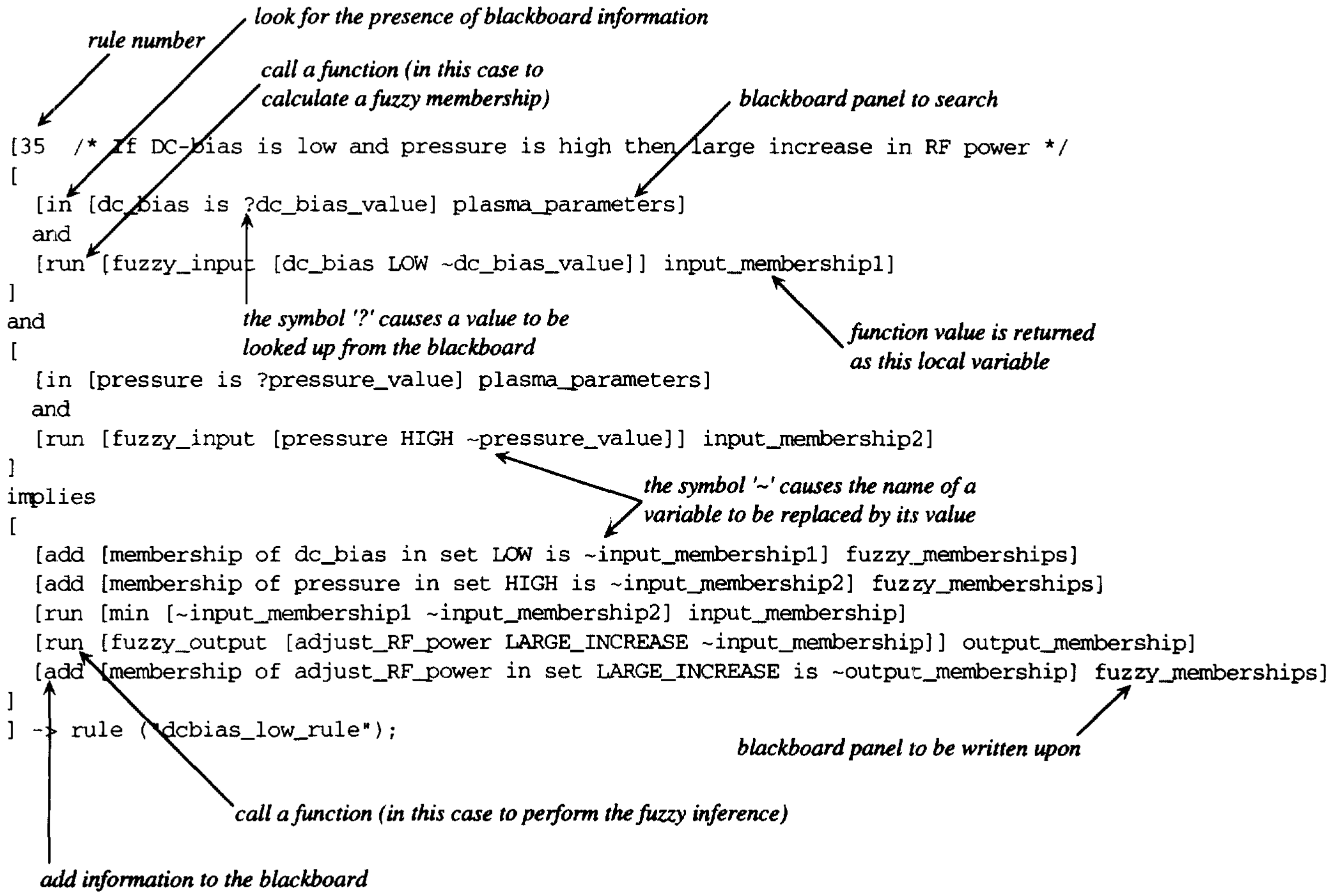
if DC-bias is LOW and RF power is LOW then LARGE DECREASE in pressure

if DC-bias is LOW and RF power is NOT LOW then DECREASE the pressure
if DC-bias is MEDIUM then DON'T CHANGE the pressure
if DC-bias is HIGH and RF power is NOT HIGH then INCREASE the pressure
if DC-bias is HIGH and RF power is HIGH then LARGE INCREASE in pressure.

Adjusting both RF power and pressure:

if DC-bias is LOW and pressure is HIGH then INCREASE the RF power and DECREASE the pressure
if DC-bias is LOW and pressure is NOT HIGH then LARGE INCREASE in RF power
if DC-bias is MEDIUM then DON'T CHANGE either the RF power or the pressure
if DC-bias is HIGH and pressure is NOT LOW then LARGE DECREASE in RF power
if DC-bias is HIGH and pressure is LOW then DECREASE the RF power and INCREASE the pressure.

Figure 5 shows how the first of these fuzzy rules has been implemented in ARBS, including the reading and updating of the blackboard. In order to demonstrate that fuzzy logic could be implemented in ARBS without changing the underlying system at all, the `fuzzy_input` and `fuzzy_output` functions are shown as explicit algorithms. These functions (along with `min`, `max` and `not` for conjunctions, disjunctions and negations



```
[35  /* If DC-bias is low and pressure is high then large increase in RF power */
[
  [in [dc_bias is ?dc_bias_value] plasma_parameters]
  and
  [run [fuzzy_input [dc_bias LOW ~dc_bias_value]] input_membership1]
]
and
[
  [in [pressure is ?pressure_value] plasma_parameters]
  and
  [run [fuzzy_input [pressure HIGH ~pressure_value]] input_membership2]
]
implies
[
  [add [membership of dc_bias in set LOW is ~input_membership1] fuzzy_memberships]
  [add [membership of pressure in set HIGH is ~input_membership2] fuzzy_memberships]
  [run [min [~input_membership1 ~input_membership2] input_membership]
  [run [fuzzy_output [adjust_RF_power LARGE_INCREASE ~input_membership]] output_membership]
  [add [membership of adjust_RF_power in set LARGE_INCREASE is ~output_membership] fuzzy_memberships]
]
] -> rule ("dcbias_low_rule");
```

Fig. 5. A fuzzy rule in ARBS: "if DC-bias is LOW and pressure is HIGH then LARGE INCREASE in RF power".

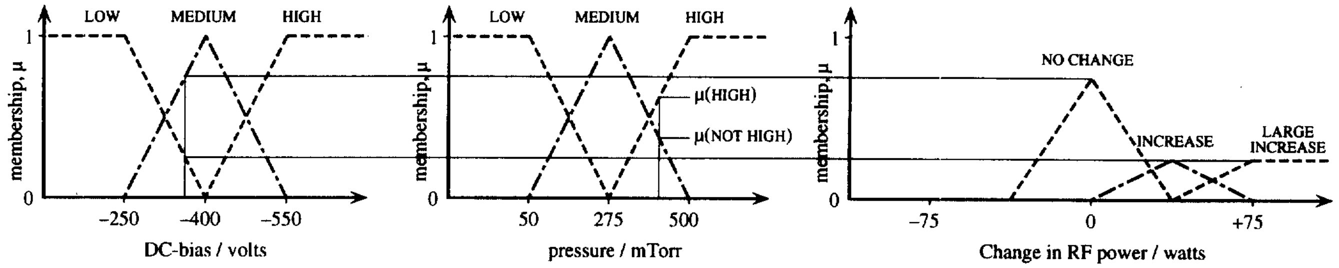


Fig. 6. Fuzzy inference using Larsen's Product Operation Rule. The rules are those for adjusting RF power only. In this example the DC-bias is − 362.5 volts and the pressure is 415.6 mTorr. Memberships of DECREASE and LARGE DECREASE in RF power are zero.

respectively) could alternatively be added to the ARBS syntax, thereby eliminating the need for the word `run` and the accompanying brackets in Fig. 5.

In ARBS, the fuzzification of the input variables (DC-bias and pressure in the above example) is carried out in a sub-condition of a rule. The chosen method of inference is Larsen's Product Operation Rule,[8] in which the membership functions of the output variable (RF power adjustment, in the above example) are multiplied by their respective membership values. The effect is to shrink the membership functions so that the peaks equal the membership values, as shown in Fig. 6 for the rules that adjust only RF power. These calculations are carried out in a sub-conclusion and the results are stored on the blackboard.

Once all relevant fuzzy rules have fired and placed their fuzzy outputs on the blackboard, a further rule, which carries out the defuzzification, becomes eligible to fire.

5 DEFUZZIFICATION

The Centre of Area (COA, or centroid)[8] method of defuzzification has been adopted in ARBS. The method involves calculating the point along the fuzzy variable axis which is the centroid of all the membership functions taken together for that variable (Fig. 7). When two membership functions overlap, some authors assume that the areas are counted twice[5,9] while other authors' diagrams imply that the overlapping area is counted only once.[10] In ARBS it is assumed that overlapping areas are counted twice.

There are at least three ways of handling membership functions which extend beyond the lower–upper range of the output variable:

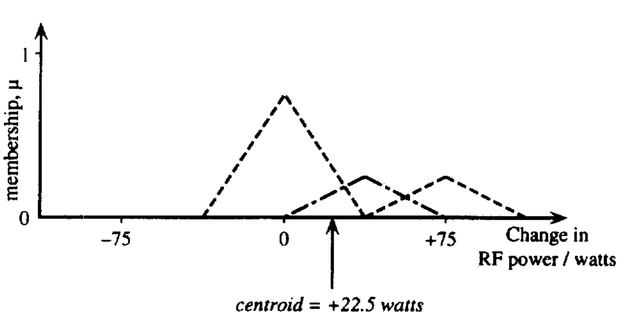


Fig. 7. Defuzzification using the COA, or centroid, method.

- assume a cut-off, so that beyond this range the membership values are 0;
- assume that the memberships that apply at the 'lower' and 'upper' values are maintained beyond the range;
- assume, *for defuzzification purposes only*, that the LOW and HIGH membership functions are symmetrical, centred on the 'lower' and 'upper' values respectively.

With the first option, the defuzzified output variable cannot reach the ends of the range using the COA method. Since the second option allows the fuzzy variable to extend to ± ∞, the COA cannot be calculated. Therefore the third option has been adopted in ARBS. This method allows the defuzzified variable to take any value over the full lower–upper range. If a fuzzy variable has a membership of 1 of the fuzzy set LOW and all other memberships are zero, its defuzzified value becomes the 'lower' value of the range.

Because the COA method can involve a lot of calculation, some authors have suggested using a look-up table[11] in order to speed up the defuzzification process. In ARBS a different approach has been adopted, in which the COA of each membership function is determined in advance. The underlying method is unchanged, but the resulting computation is very simple.

The formula for determining the position, C, of the COA is:

$$C = \frac{\int \mu x \, dx}{\int \mu \, dx}$$

where x is the variable to be defuzzified and μ is its membership function. If there are N membership functions, this can be re-written as:

$$C = \frac{\sum_{i=1}^{N} \int \mu_i x \, dx}{\sum_{i=1}^{N} \int \mu_i \, dx}.$$

If the N centroids of individual membership functions are denoted by c_i and the areas by a_i, the equation becomes:

$$C = \frac{\sum_{i=1}^{N} a_i c_i}{\sum_{i=1}^{N} a_i}.$$

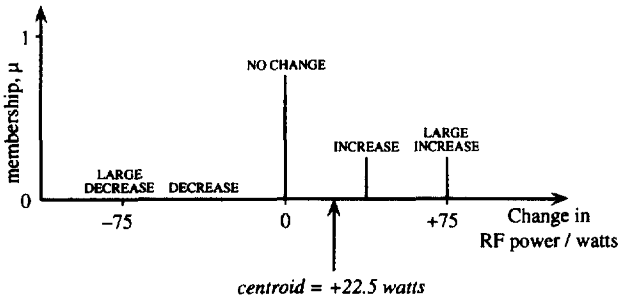


Fig. 8. Dirac delta functions in place of the triangular membership functions.

The centroid of a triangle does not move when its height is altered, so c_i is known in advance and stays constant. The area of each triangle is proportional to its height, and under Larson's product operation rule the height is scaled according to the inferred membership. So the area of each triangle is $\mu_i A_i$, where A_i is its original area prior to 'Larson shrinkage'. In ARBS, all the initial areas are the same for a given fuzzy variable and so the COA equation reduces to:

$$C=\frac{\sum_{i=1}^{N}\mu_i c_i}{\sum_{i=1}^{N}\mu_i}.$$

The areas no longer appear in the equation and each membership function has, in effect, been replaced by a Dirac delta function placed at its centroid, c_i (Fig. 8). The height of each delta function is equal to the membership of its corresponding fuzzy set.

In the example shown in Fig. 8, the defuzzified change in RF power, ΔP, is given by:

$$\Delta P=\frac{[0\times(-75)]+[0\times(-37.5)]+[0.75\times 0]+[0.25\times 37.5]+[0.25\times 75]}{0+0+0.75+0.25+0.25}=+22.5\text{ watts.}$$

6 FUZZY CONTROL OF PLASMA DEPOSITION PROCESSES

As shown in Section 4, three alternative sets of fuzzy rules have been implemented for controlling DC-bias by

(i) adjustment of RF power,

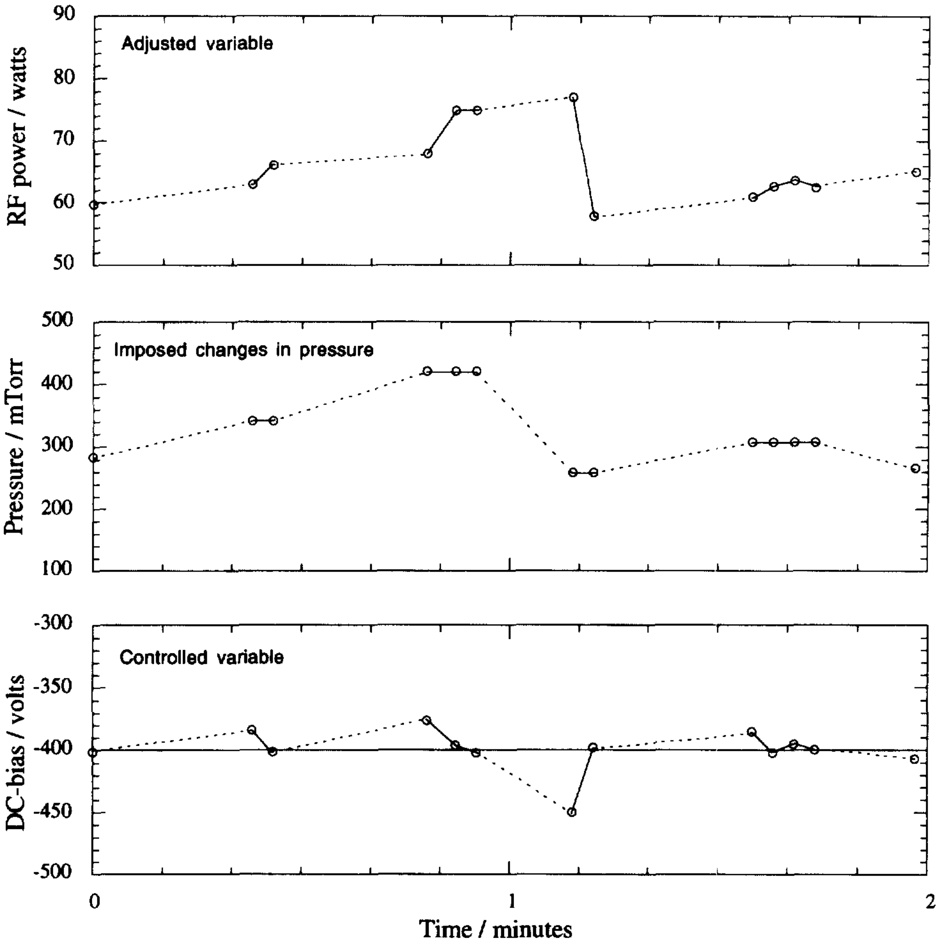


Fig. 9. Fuzzy control of DC-bias by adjustment of RF power.

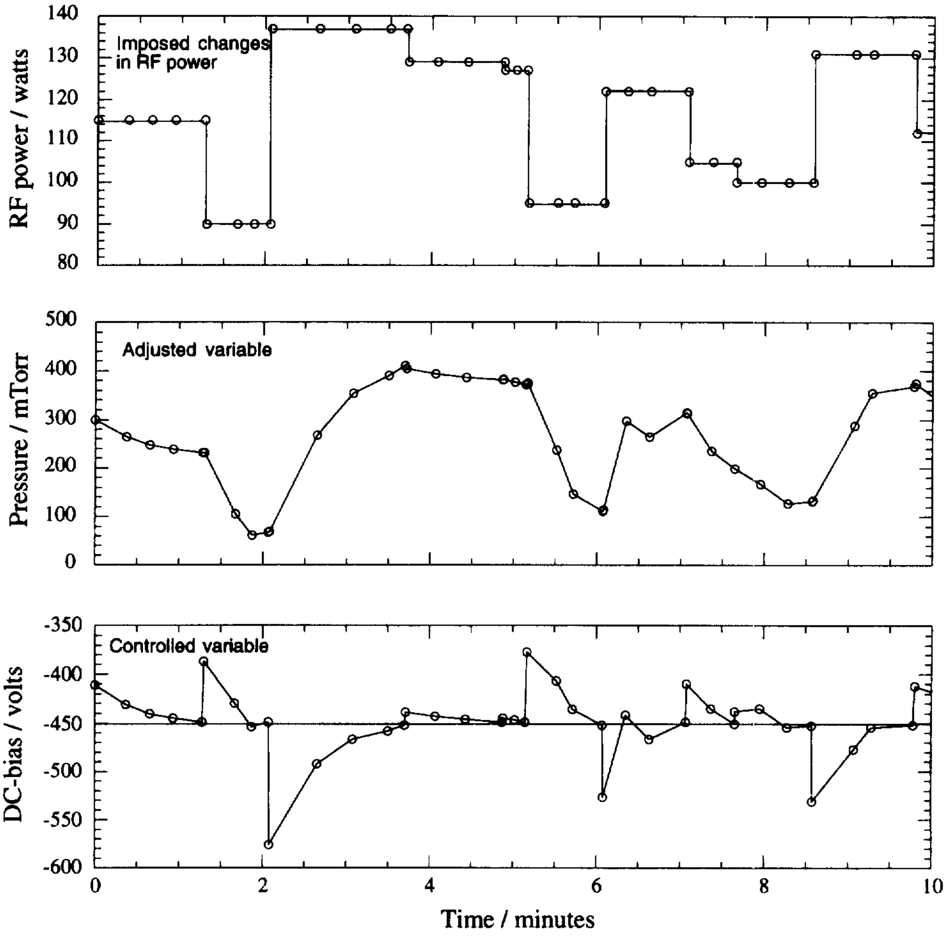


Fig. 10. Fuzzy control of DC-bias by adjustment of pressure.

(ii) adjustment of pressure,

(iii) adjustment of both of these parameters simultaneously.

In each case the fuzzy rules have been placed in a knowledge source which also contains 'crisp' rules for:

- recording plasma conditions,
- checking that the adjusted RF power remains within safe limits,
- recognising when the DC-bias has reached its goal value.

The three fuzzy controllers were tested by deliberately perturbing the DC-bias of the plasma unit through imposed changes in pressure and/or RF power. Figures 9–11 show the response of the three fuzzy controllers as they returned the plasma to the desired DC-bias (either −400 or −450 volts). The response time is primarily a characteristic of the physics of the plasma unit. Changes in pressure are comparatively slow so, for the purpose of the test shown in Fig. 9, control was suspended while the imposed pressure perturbations were achieved. These delays are indicated by the dashed lines in Fig. 9. In the case where both pressure and RF power are adjusted, it can be seen from Fig. 11 that there is not a unique solution, as the controller settles on different pairs of values of pressure and RF power after each perturbation.

The performance of the fuzzy controllers is comparable with a PID controller used elsewhere for a similar task.[12] A detailed quantitative comparison is not attempted here, as the performance of a PID controller is strongly dependent on its operating parameters, whilst the performance of a fuzzy controller depends on the sophistication of its rules and the specification of its fuzzy sets. Although both approaches can control a plasma, the key difference is that the fuzzy controllers have achieved this without recourse to time-consuming tuning and optimisation. The fuzzy controllers are therefore a generic solution, which can be readily applied to different equipment and/or geometries. A PID controller, on the other hand, would need to be re-tuned and re-optimised for each application.

7 CONCLUSIONS

Fuzzy logic has been incorporated into ARBS, an existing in-house blackboard system. As ARBS allows access to external algorithms from within rules, it has been possible to do this without making any alterations to the existing software, thus demonstrating the flexibility of this implementation of a blackboard system.

As fuzzy rules and crisp rules are implemented in the same manner, both types of rule can coexist within the

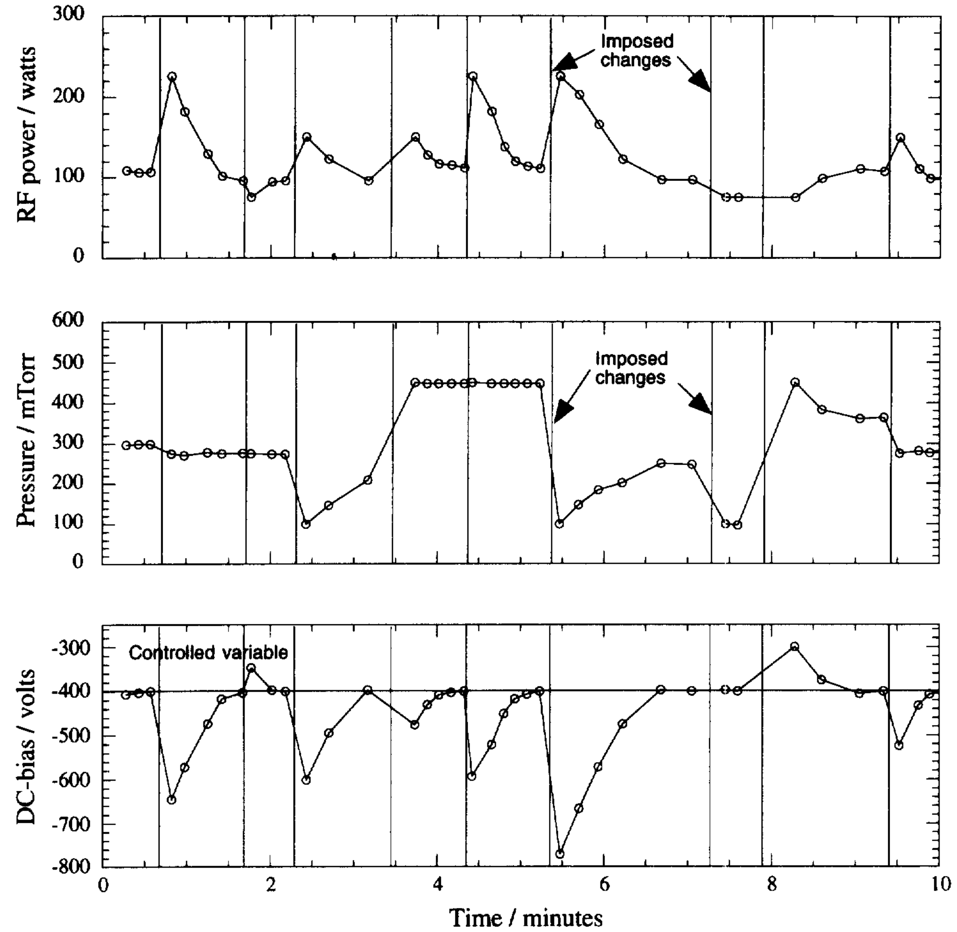


Fig. 11. Fuzzy control of DC-bias by adjustment of both pressure and RF power.

same knowledge source. Similarly, crisp and fuzzy logic can be mixed within rules, so that a single rule may contain both fuzzy and non-fuzzy sub-conditions and sub-conclusions.

An efficient technique for defuzzification has been employed which adheres to standard underlying methods but which reduces the number of calculations required without loss of precision or accuracy.

ARBS has been applied to fuzzy control of a plasma deposition process. The fuzzy controller is effective at maintaining DC-bias (an intermediate variable of the plasma) at its set point by adjusting either the RF power, or the pressure, or both parameters simultaneously. In each case, a knowledge source containing fuzzy and non-fuzzy rules has been used.

ACKNOWLEDGEMENTS

This work was funded by the EPSRC under grant reference GR/J32213 and by the Open University Research Committee. The authors are grateful to the referees of this paper for their helpful comments.

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