

FUZZY CONTROL OF THE ACTIVATED  
SLUDGE WASTEWATER TREATMENT  
PROCESS

R.M. Tong  
M.B. Beck  
A. Latten

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INTERNATIONAL INSTITUTE FOR APPLIED SYSTEMS ANALYSIS  
A-2361 Laxenburg, Austria

M.B. BECK is a research scientist at the International Institute for Applied Systems Analysis, Schloss Laxenburg, 2361 Laxenburg, Austria.

A. LATTEN is the manager of Whitlingham Treatment Works, Anglian Water Authority, Trowse, Norwich, United Kingdom.

R.M. TONG is with the Electronics Research Laboratory, University of California, Berkeley, California 94720, USA.

## PREFACE

Two previous papers (IIASA Professional Papers PP-78-10 and PP-79-3) have reported some of the results from a small collaborative project investigating the modeling and control of the activated sludge process of wastewater treatment. This brief paper provides a more detailed evaluation of a fuzzy controller for the activated sludge process. Such an approach to process control utilizes the empirical operating experience of the plant manager. Most conventional control system design procedures, in contrast, are based upon analysis of a model of process dynamic behavior. Given the current limitations in understanding and instrumentation of the activated sludge process, fuzzy control appears to be a particularly appropriate approach to adopt for process control.



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## SUMMARY

The activated sludge process is a commonly used method for treating sewage and waste waters. It is characterized by a lack of relevant instrumentation, control goals that are not always clearly stated, the use of qualitative information in decision making and poorly understood basic behavior mechanisms. In this brief paper we examine the behavior of an experimental fuzzy control algorithm constructed to reflect actual operational practice. We conclude that this algorithm does rather well and that a fuzzy controller would be a useful and practical way of regulating the activated sludge process.





## 1. Introduction.

Fuzzy controllers have been successfully used in a variety of applications (see Tong, 1977 for a review). In all of these applications, however, the control goals were clearly specified, accurate and reliable measurements of the relevant process variables were available and, perhaps more importantly, none of the controlled processes had more than two inputs or two outputs. It would be hard to argue, therefore, that these were "difficult" control problems. Nonetheless, the success has encouraged the belief, at least amongst its advocates, that the fuzzy approach can be used on a wide variety of processes.

In this paper we report on some results from a continuing study of the role of fuzzy set theory in the control of the activated sludge wastewater treatment process (ASP). The ASP is characterized by a lack of relevant instrumentation, control goals that are not always clearly stated, the use of qualitative information in decision making and poorly understood basic behavior mechanisms. As such, it appears to be an ideal candidate for fuzzy control and is certainly a more severe test of the methodology than previous applications.

Section two of the paper outlines the behavior of the ASP and highlights the principal control problems. Section three discusses one particular controller with which we have experimented and analyzes some of the resulting closed loop responses. We then make some general comments on the design of fuzzy controllers.

## 2. The Activated Sludge Wastewater Treatment Process.

The ASP is one of a number of unit processes used for the treatment of sewage and waste waters. The basic feature of the process is the decomposition of complex dissolved and suspended organic substrates into simple end-products such as carbon dioxide and water. Decomposition is achieved by a heterogeneous culture of micro-organisms (the activated sludge), which in part utilize the waste organic substrates in the synthesis of their own biological cell material.

Our studies have been concerned primarily with a particular ASP plant at the Whitlingham Treatment Works, Norwich, England. This installation is shown diagrammatically in Figure 1. If we consider only that part of the diagram within the dotted lines, we see that there are two stages in the overall process: an aeration tank followed by a clarifier/settler. Correct operation of the process requires, among other things, the following three items. First, the influent sewage entering the process has to be mixed intimately with the recycled sludge; in principle there exist ranges of desirable proportions in which substrate (sewage) and organism (sludge) should be mixed (Cashion, Keinath, and Schuk, 1977). Second, air is blown into the mixed liquor through diffusers placed along the base of the tank; this gives the required agitation of the mixed liquor, provides the necessary aerobic environment for growth of the sludge organisms, and can be a key factor in operational control (Olsson and Andrews, 1978). Third, the settler must effect good separation between the biological floc (sludge)

and the clarified effluent; excess biological solids in the ASP may be manipulated by the removal of waste sludge. Recent work on the application of automation and control to the ASP is surveyed by Olsson (1977).

Local control action is taken at the Norwich ASP to help achieve these aims. Thus, as shown in Figure 1, recycle sludge ratio (defined as the ratio of influent flow rate,  $Q_I$ , to recycled sludge flow rate,  $Q_R$ ) is regulated by feedforward control of  $Q_R$  using measurements of  $Q_I$ . Dissolved oxygen (DO) in the aeration tank is regulated by feedback control of the airblowers using a measurement of DO. Waste sludge flow,  $Q_W$ , is set by the plant manager.

An ASP that is performing as required will be producing an effluent that meets some standard. In Britain, this is simply a recommendation that the total (5-day) biochemical oxygen demand exerted by the effluent should be less than  $20 \text{ gm}^{-3}$  and that the amount of suspended solid material in the effluent should be less than  $30 \text{ gm}^{-3}$ . Whilst these are hard constraints on the process, a plant manager can choose to operate as close to them as he feels is practical. In a real sense, therefore, there is some fuzziness associated with these values. There are secondary goals, but these will differ from installation to installation and will depend primarily on the quality and type of sewage that the process receives. However, one of the most important of these is that ammonia in the effluent is kept at acceptable levels.

The major disturbances to the process are in the form of fluctuations in the composition and flow of the influent.

There are short term diurnal variations as well as long term trends which together can easily produce changes of up to 50% in the average quality of the influent.

Our control problem is thus simply stated. How can we manipulate recycle ratio set point (RRSP), dissolved oxygen set point (DOSP) and waste sludge flow (SWR) so that we maintain effluent quality despite these large variations in the influent?

### 3. The Fuzzy Controller

At the core of the controller is a fuzzy algorithm for determining the appropriate control actions given the current state of the process. Because the algorithm expects fuzzy sets as inputs, the non-fuzzy process measurements have to be converted in some way. We have adopted the conventional technique of representation by fuzzy singletons. Similarly, since the process responds only to non-fuzzy control actions, the fuzzy control sets generated by the algorithm have to be de-fuzzified. We do this by selecting that control value which divides the area under the membership function in half. The closed loop configuration is thus as shown in Figure 2.

The basic design problem is to construct the fuzzy algorithm. In doing this we have relied on the considerable practical experience of one of us (AL) in the day-to-day management of the ASP. The first task is to determine the fuzzy input (measurement) variables for the algorithm, the fuzzy output (control) variables and the primary fuzzy sets associated with

each of these. The set definitions have not been included here because of space limitations; however, the input and output variables are listed in Table 1.

We have experimented with several algorithms but will restrict our discussion to one that has several interesting features. It is shown in Table 2 and consists of 20 rules. Symbols such as S,  $\sim$ L and SP are mnemonics for fuzzy sets which in this case are "small," "not large" and "small positive." Each rule in the algorithm is interpreted as a fuzzy statement of the form

WHEN  $\underline{Y}$  DO  $\underline{U}$

where  $\underline{Y}$  is a fuzzy proposition about process conditions in terms of the measurements and where  $\underline{U}$  is a fuzzy proposition about appropriate control actions. The propositions are interpreted as multi-dimensional fuzzy sets and the rule itself is defined as their cartesian product. Individual rules are combined using the union (maximum) operation to form the overall controller relation.

The reasoning behind the algorithm is briefly as follows (for a more detailed description of the role of similar rules see Beck, Latten, and Tong, 1978). Rules 1-3 are resetting rules in that, if the process is in a satisfactory state but DOSP and/or SWR are at abnormal levels, then DOSP and/or SWR are adjusted accordingly. Rules 4-7 deal with high effluent suspended solids caused by a rising or bulking sludge (these terms are briefly defined in Table 1). Rules 8-11 deal with high  $\text{NH}_3\text{-N}$  levels in the effluent. Rules 12-13 cater for high

effluent solids caused by factors other than FIL or DNIT and rules 14-18 describe the required control action if MLSS is outside its normal range. Rules 19-20 deal with the problem of a high effluent BOD.

Notice that most rules are concerned with changes to SWR. This reflects the fact that in practice waste sludge flow is used most often to correct for effluent quality variations. Notice too, that the rule set does not, by any means, exhaust all the possible process states. It may be thought of as a "sparse algorithm." To test this algorithm we ran a simulation of the ASP using a non-linear differential equation model (with 14 state variables) and applying a disturbance sequence derived from corresponding observations recorded at the Norwich plant. Conceptual aspects of the model are described in Beck, Latten, and Tong (1978); some accompanying identification results are reported in Beck (1979).

Figure 3 shows thus the open loop response of ESS and ETBD on an hourly basis for 600 hours (i.e., 25 days). Clearly, the process is not functioning properly. There are large excursions in both ESS and ETBD in the early and late parts of the simulation (caused in fact by a bulking sludge condition). Also,  $\text{NH}_3\text{-N}$  levels in the effluent are high except for the first 100 hours.

The controlled responses to the same disturbance sequence are shown in Figures 4-6. The controller sampling period is set at 4 hours in this run (i.e., six possible changes in control action in each 24 hours). Figure 4 shows the hourly ESS and ETBD values; Figure 5 shows the hourly  $\text{NH}_3\text{-N}$  and MLSS

values and Figure 6 shows the corresponding values of RRSP, DOSP and SWR. Notice, straight away, that the early and late bulking sludge conditions have been suppressed. Notice too that the ETBD and ESS levels are well within the 20:30 limits, except for three occasions between 400 hours and 475 hours. These three occasions, which represent a significant loss of solids over the clarifier weir, are precipitated by problems of a rising and a bulking sludge, with both problems being partly a complex function of over-aeration (see DOSP in Figure 6). There is generally good nitrification throughout the period with  $\text{NH}_3\text{-N}$  rarely being above  $15 \text{ gm}^{-3}$ .

Our preliminary conclusion must be that the controller works rather well. However, it does have some defects and in exploring these we shall make use of an analytical tool which we call a "rule activity chart." Figure 7 shows the rule activity for  $\Delta\text{DOSP}$  (top two traces) and for  $\Delta\text{RRSP}$  (lower four traces). Figure 8 shows the rule activity for  $\Delta\text{SWR}$ . The horizontal axis is time and the vertical axis is the degree to which the input proposition  $\underline{y}$  is satisfied. Thus these charts tell us which rules are contributing to the non-fuzzy control actions applied to the process.

Since in this paper we are primarily concerned with the operational aspects of the fuzzy algorithm, rather than a detailed analysis of the ASP's responses, we shall limit ourselves to a discussion of just two features of the closed loop behavior. Despite our assertion that in practice SWR is the most often used control variable, we see from Figure 6

that RRSP is frequently changed. The activity charts of Figure 7 indicate that this is primarily due to rules 12 and 17. But notice that these rules are often activated at very low levels. This suggests that we might introduce some kind of threshold for rule activation.

A way of doing this that is consistent with the fuzzy set theory is to employ the concept of "truth qualification" (see Zadeh, 1978). Thus we can modify the rules in our algorithm so that they have the form

WHEN Y is  $\tau$  DO U

where  $\tau$  is a fuzzy truth set which modifies the proposition Y to give Y<sup>+</sup>. Following Zadeh, Y<sup>+</sup> is defined by a membership function such that

$$\mu_{\underline{Y}^+}(y) = \mu_{\tau}(\mu_{\underline{Y}}(y)) \quad .$$

A suitable choice for  $\tau$  will achieve the desired effect (e.g.,  $\mu_{\tau}(t) = t$  if  $t \geq$  threshold,  $\mu_{\tau}(t) = 0$  if  $t <$  threshold).

We believe that this technique could have been applied to all the fuzzy controllers that have been reported. Because it allows us to weight the importance of individual rules, it is a very flexible and useful design tool.

The second point we should like to highlight is the behavior of the control variable SWR. A comparison of the two responses shows that SWR is highly correlated with MLSS but lags it by approximately 20 hours (see Figures 5 and 6). There are two main reasons for this. Firstly, because of the



incremental form of the rules for SWR it takes time for SWR to achieve the necessary levels demanded by the process conditions. Then secondly, because the rules do not take into account rate-of-change of MLSS they cannot distinguish between a condition in which action is required (e.g., MLSS low and decreasing) and one in which it is probably not (e.g., MLSS low but increasing). Thus SWR is being changed long after such changes are required. Consequently, it is felt that in general an incremental fuzzy algorithm should take account of both the level and rate-of-change of the appropriate measured variables. We note that many of the published algorithms do exactly this.

Obviously, there are many other features of these responses which are of interest. However, they require a detailed understanding of the ASP and are outside the scope of this paper.

#### 4. Conclusions.

Our aim in this brief paper has not been to present a final solution to the ASP control problem. Rather it has been to show that a fuzzy algorithm based on practical experience can be made to work on this difficult process. In doing so, we have made some general comments about the form and structure that fuzzy algorithms should take.

Our results must clearly be qualified by the fact that evaluation of the controller has been undertaken with a process simulation. The present level of accuracy for such models for biological waste treatment processes is but little advanced beyond the primitive stage. Nevertheless, we do not

hesitate in asserting that a fuzzy algorithm would be a useful and practical way of regulating the activated sludge process. Indeed, a recent survey of factors limiting wastewater treatment plant performance by Hegg, Rakness and Schultz (1978) lends substantial support to our argument. They observed, in particular, that:

"The highest ranking factor contributing to poor plant performance was operator application of concepts and testing to process control."

". . . present plant personnel are an untapped source for achieving improved performance."

TABLE 1.

<u>Input Variable</u>	<u>Description</u>
ETBD	the total BOD exerted by the effluent
ESS	the suspended solids in the effluent
MLSS	the suspended solids in the sludge leaving the aeration tanks (the mixed liquor)
RASS	the suspended solids in the recycled sludge
NH <sub>3</sub> -N	the ammonia-N in the effluent
FIL	a measure of a condition in the clarifier called "bulking sludge"; this is caused by the presence of filamentous bacteria which prevent settling.
DNIT	a measure of a condition in the clarifier called "rising sludge"; this is caused by denitrification whereby nitrogen gas is formed and then rises to the surface of the clarifier bringing sludge with it.
DOSP	the DO set point in the aeration tank
SWR	the waste sludge flow rate
<u>Output Variable</u>	<u>Description</u>
DOSP	change in DOSP; i.e., $DOSP(t) = DOSP(t-1) + \Delta DOSP(t)$
RRSP	change in recycle ratio set point; i.e., $RRSP(t) = k + \Delta RRSP(t)$ where k is a constant

SWR

change in SWR; i.e.,  $SWR(t) = SWR(t-1) + \Delta SWR(t)$

TABLE 2.

Rule No.	ETBD	ESS	MLSS	RASS	NH <sub>3</sub> -N	FIL	DNIT	DOSP	SWR	ΔDOSP	ΔRRSP	ΔSWR
1	S	S	M	M	S			L		LN		
2	S	S	M	M	S				S			SP
3	S	S	M	M	S				L			SN
4		M					1					SP
5		L					1					LP
6		M				1				SN		
7		L				1				LN		
8		S			M					SP		
9		S			M							SN
10		S			L					LP		
11		S			L							LN
12	L	M									SP	
13	L	L									LP	
14			L									LP
15			S									SN
16			VS									LN
17			VS						S		SP	
18			L						L		SN	
19	M	S			S							SN
20	L	S			S							LN

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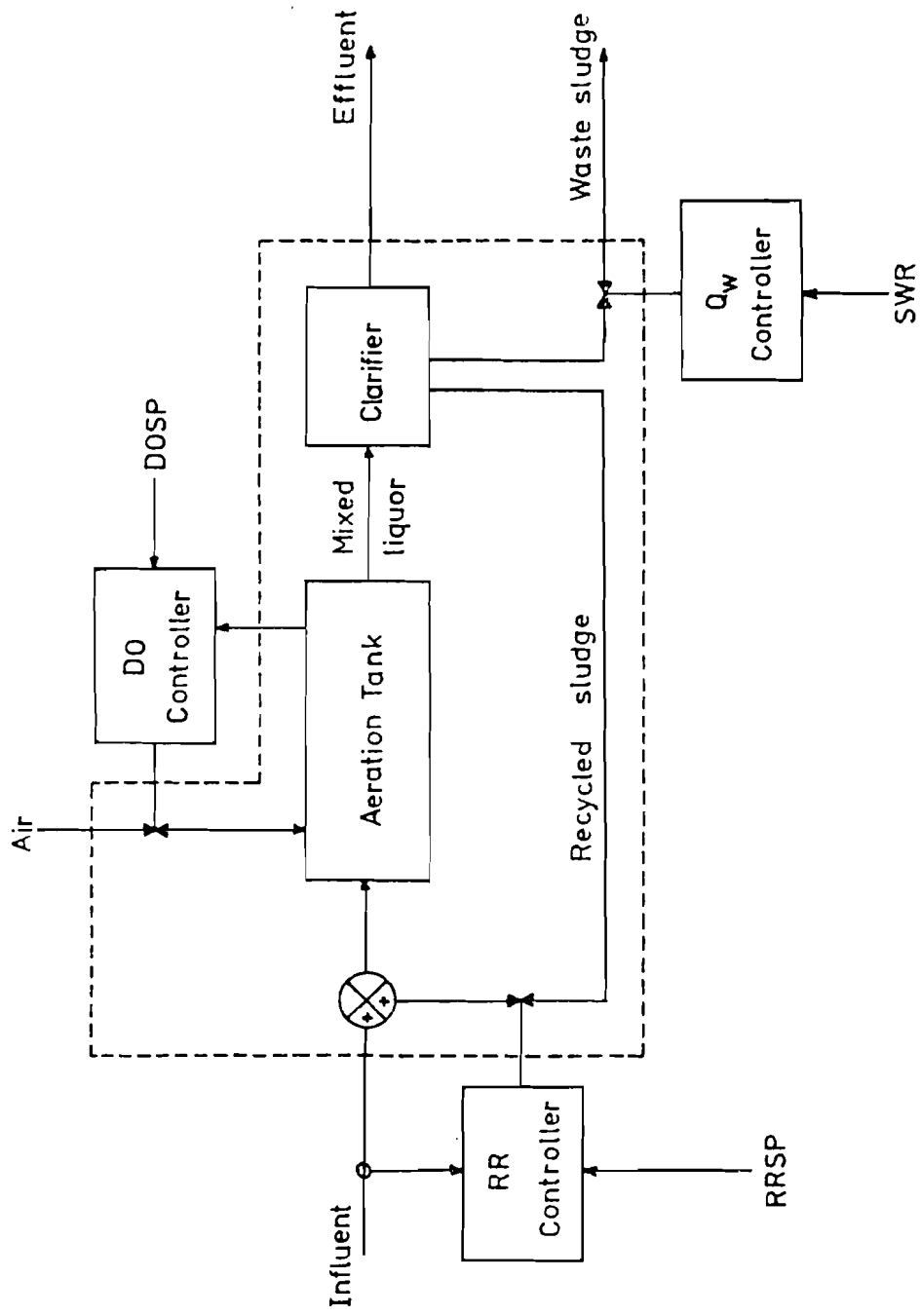


Figure 1. Schematic of the Norwich ASP.

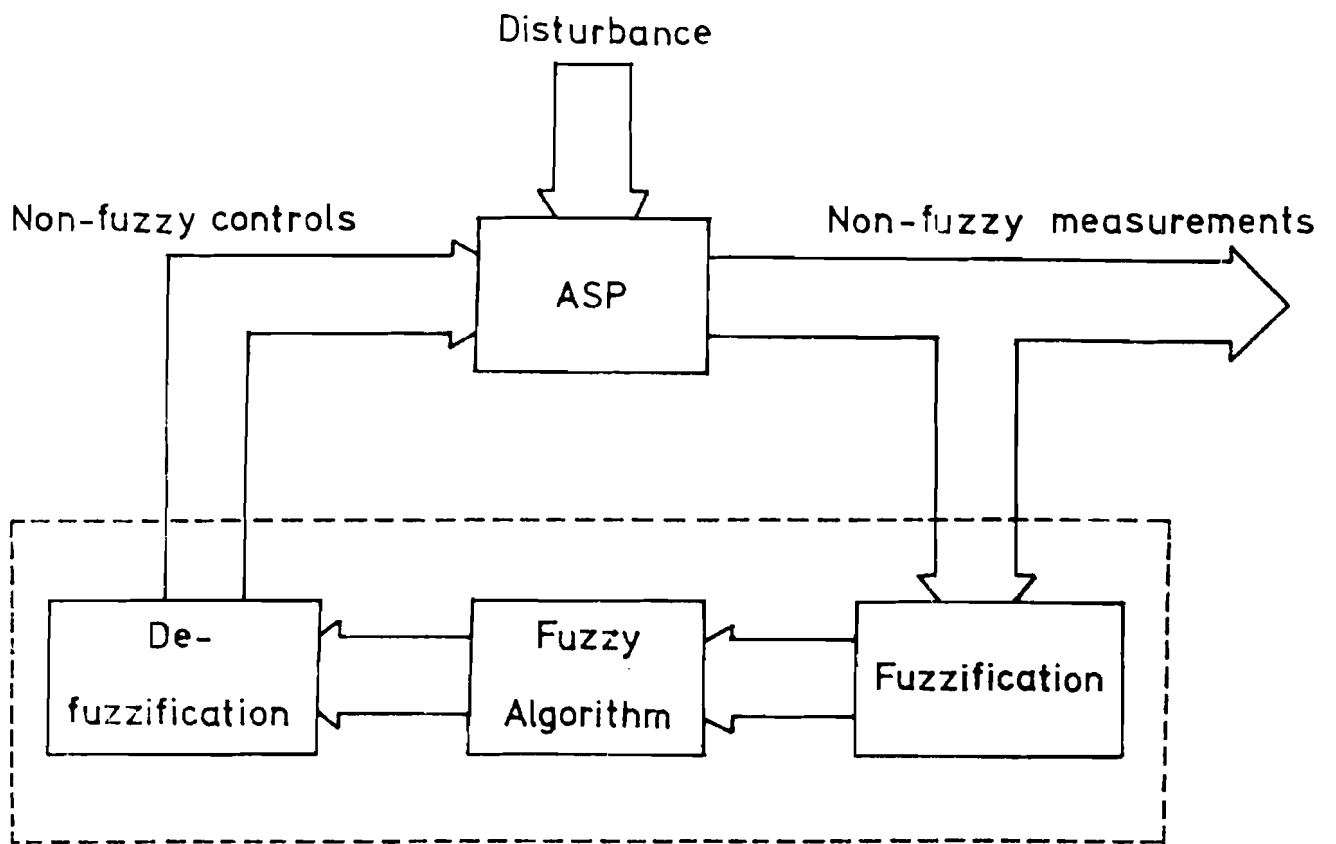


Figure 2. Closed loop configuration.



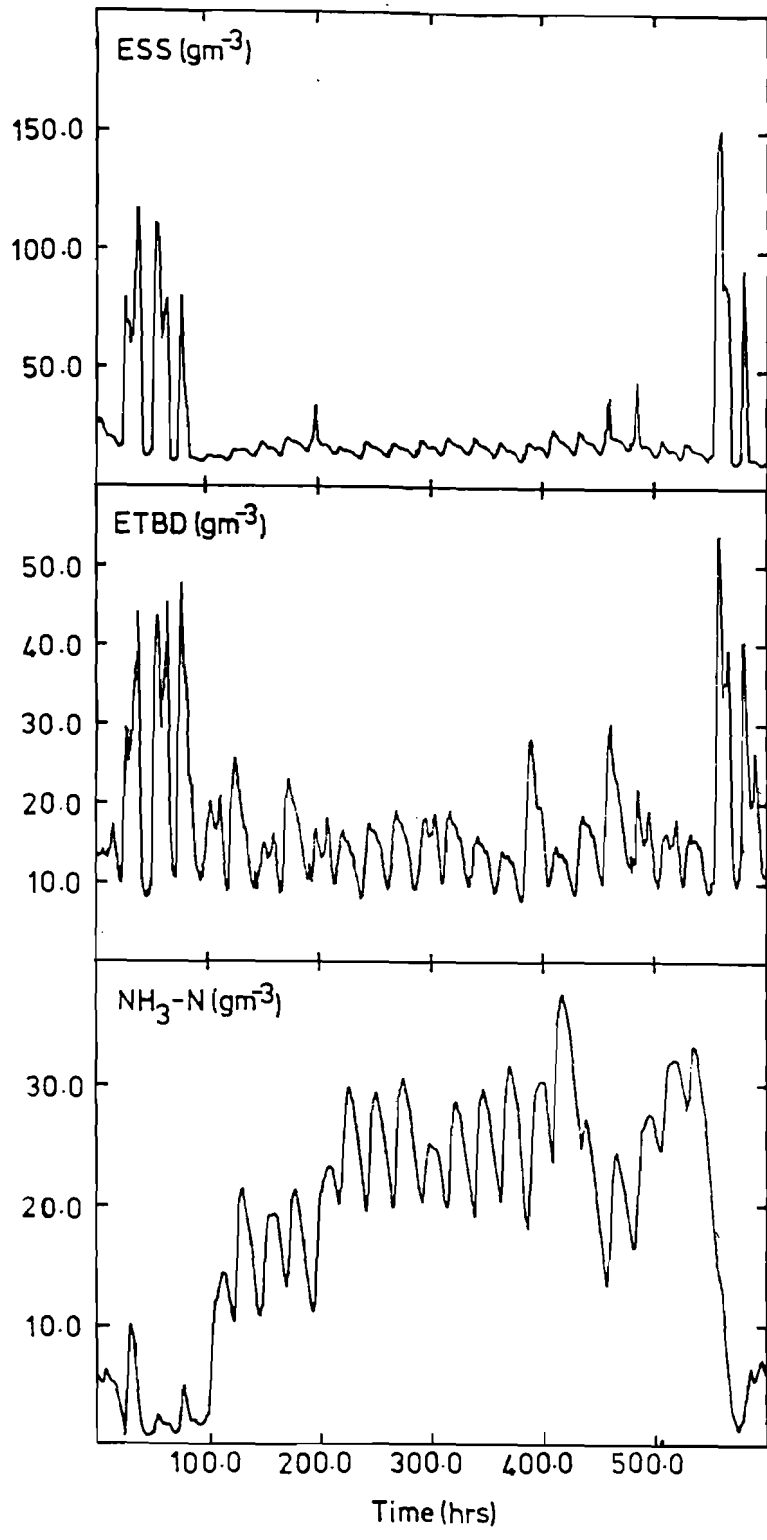


Figure 3. Open loop responses.

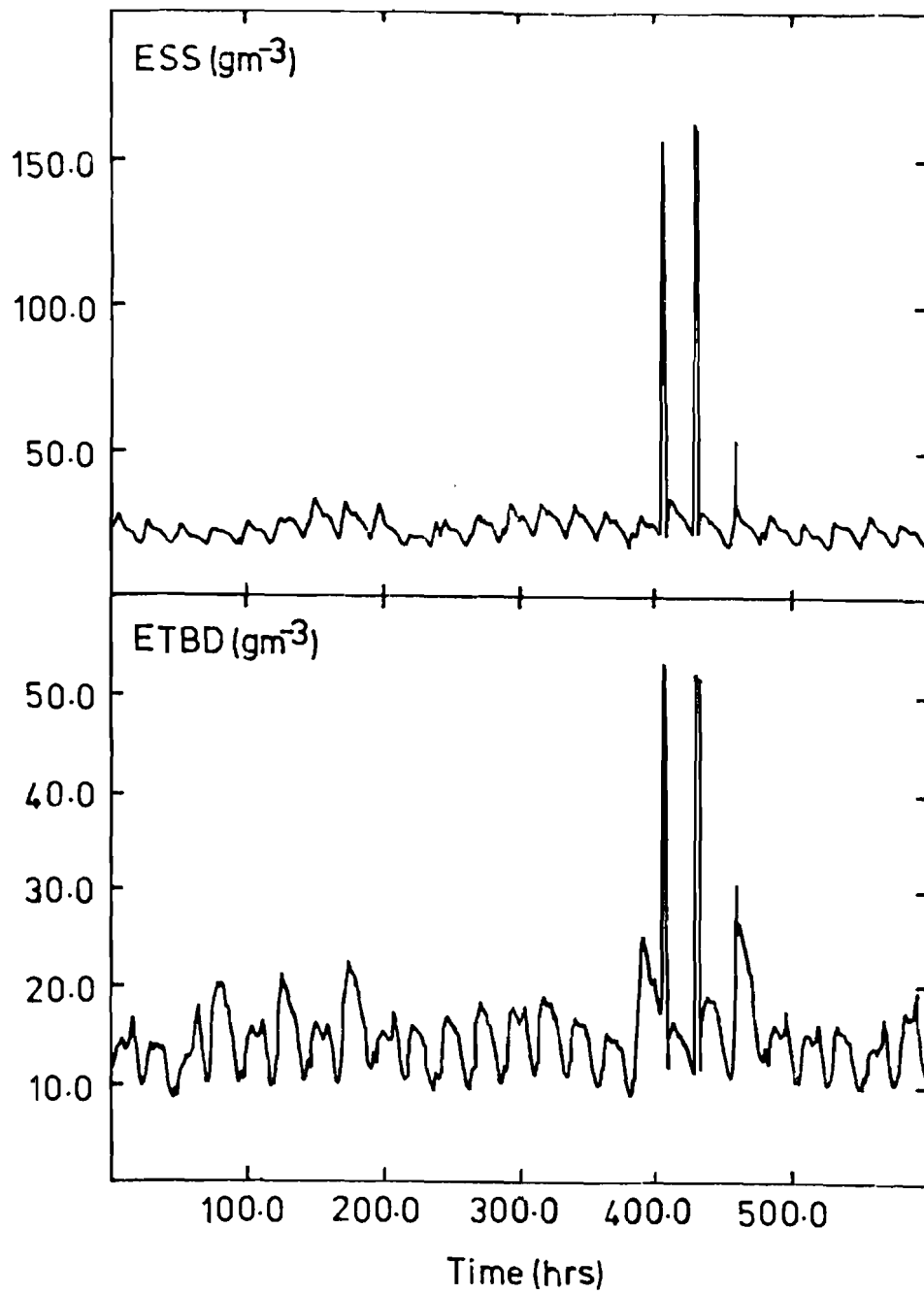


Figure 4. Closed loop responses: I.

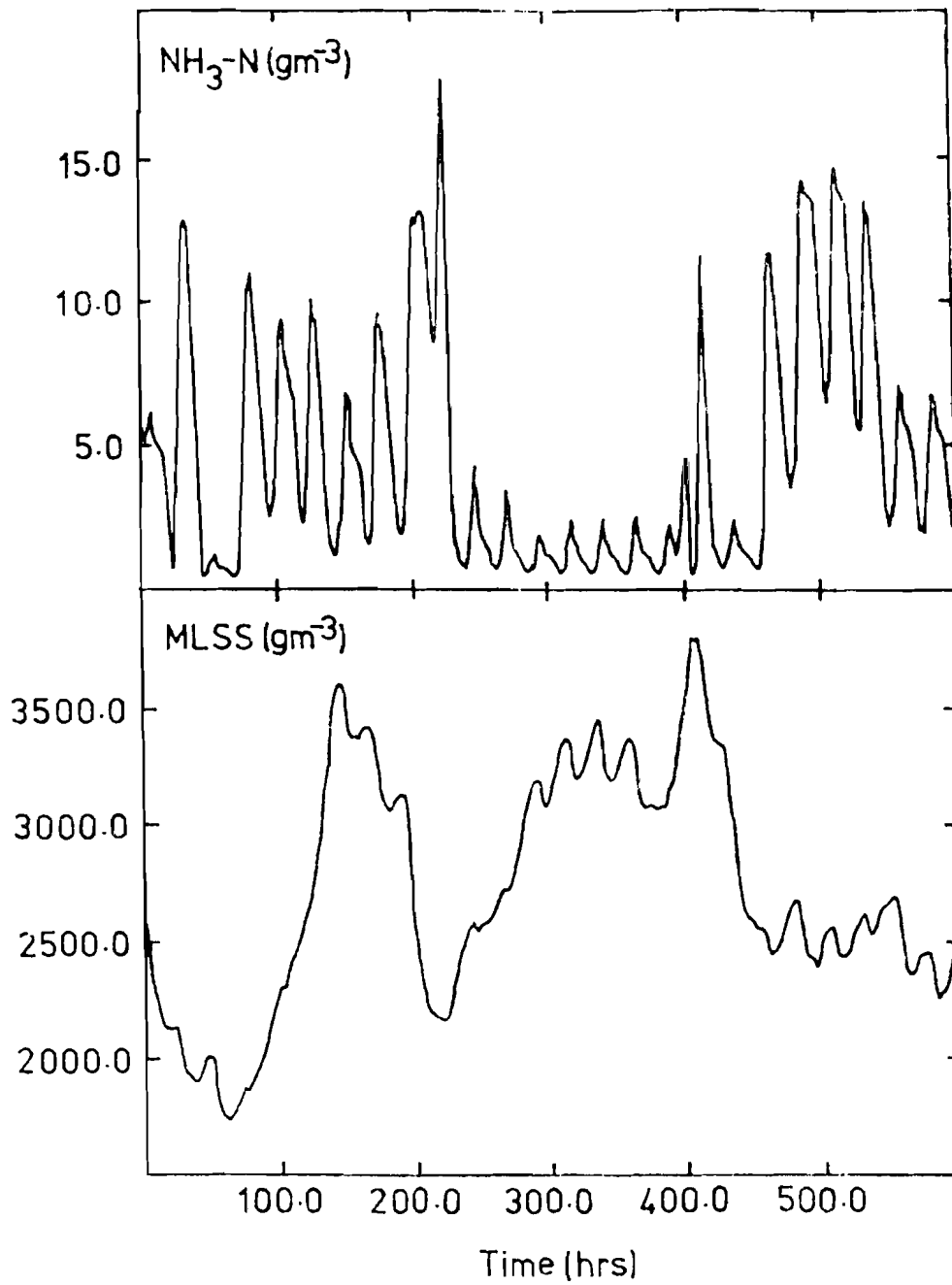


Figure 5. Closed loop responses: II.

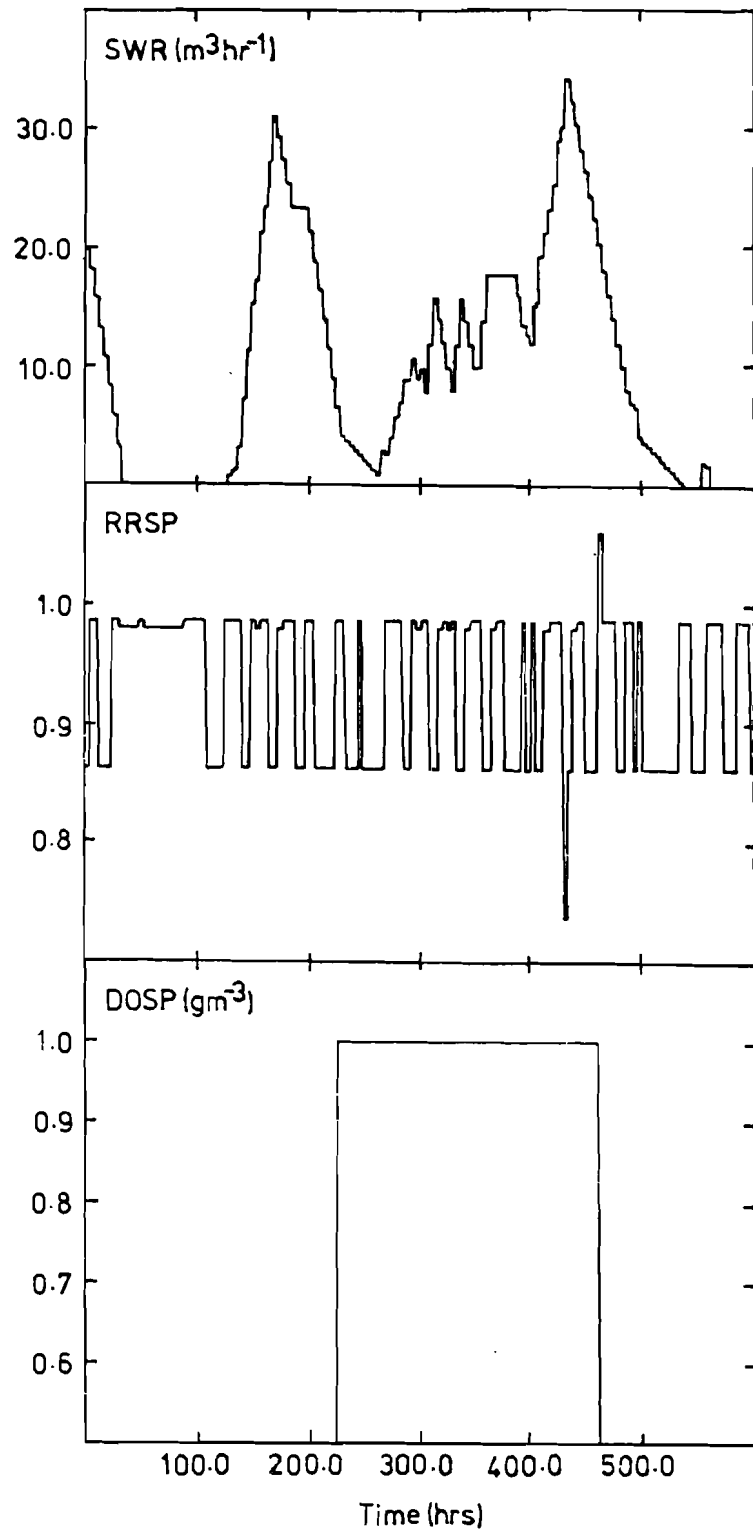


Figure 6. Closed loop control actions.

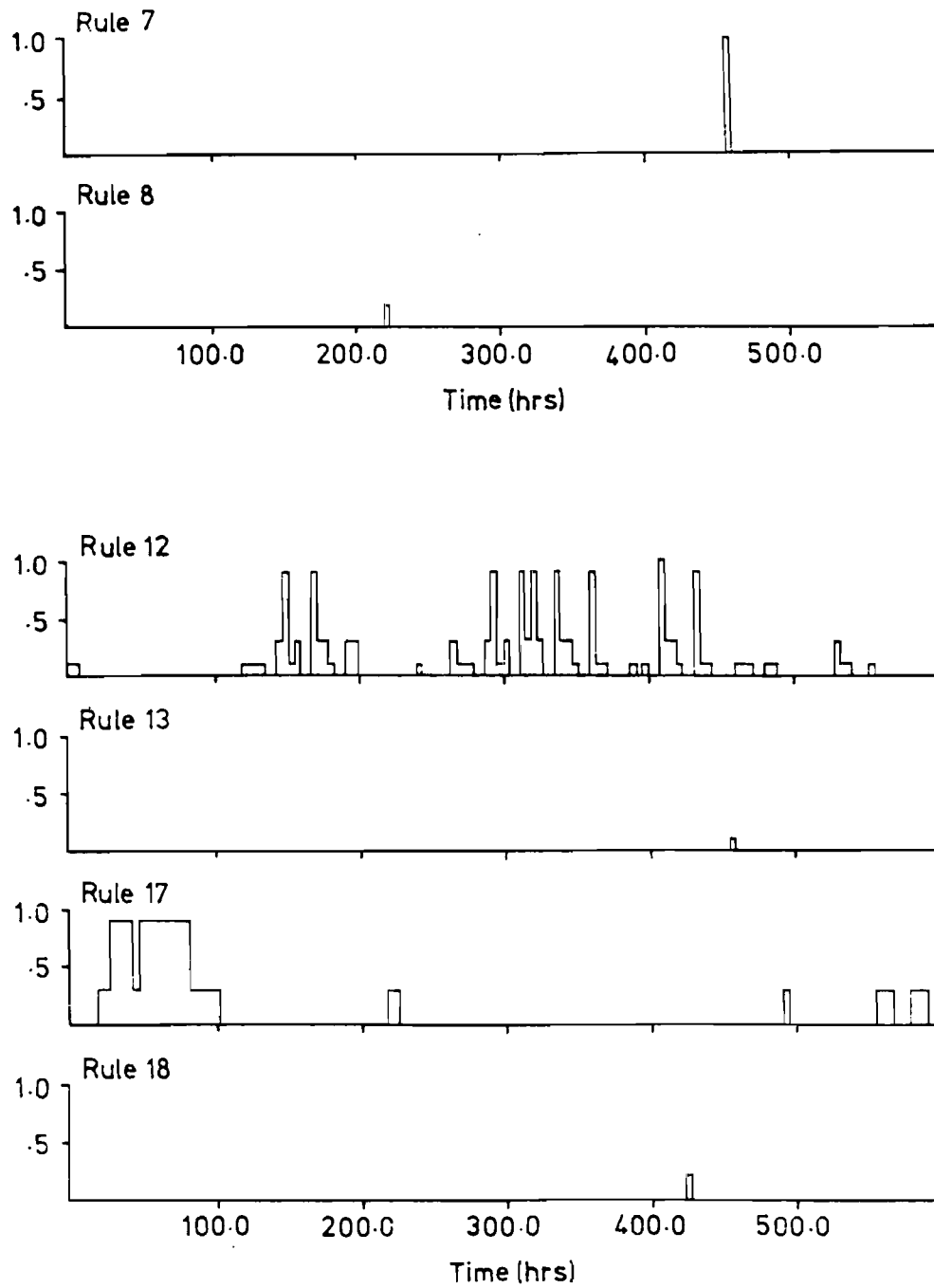


Figure 7. Rule activity chart: I.

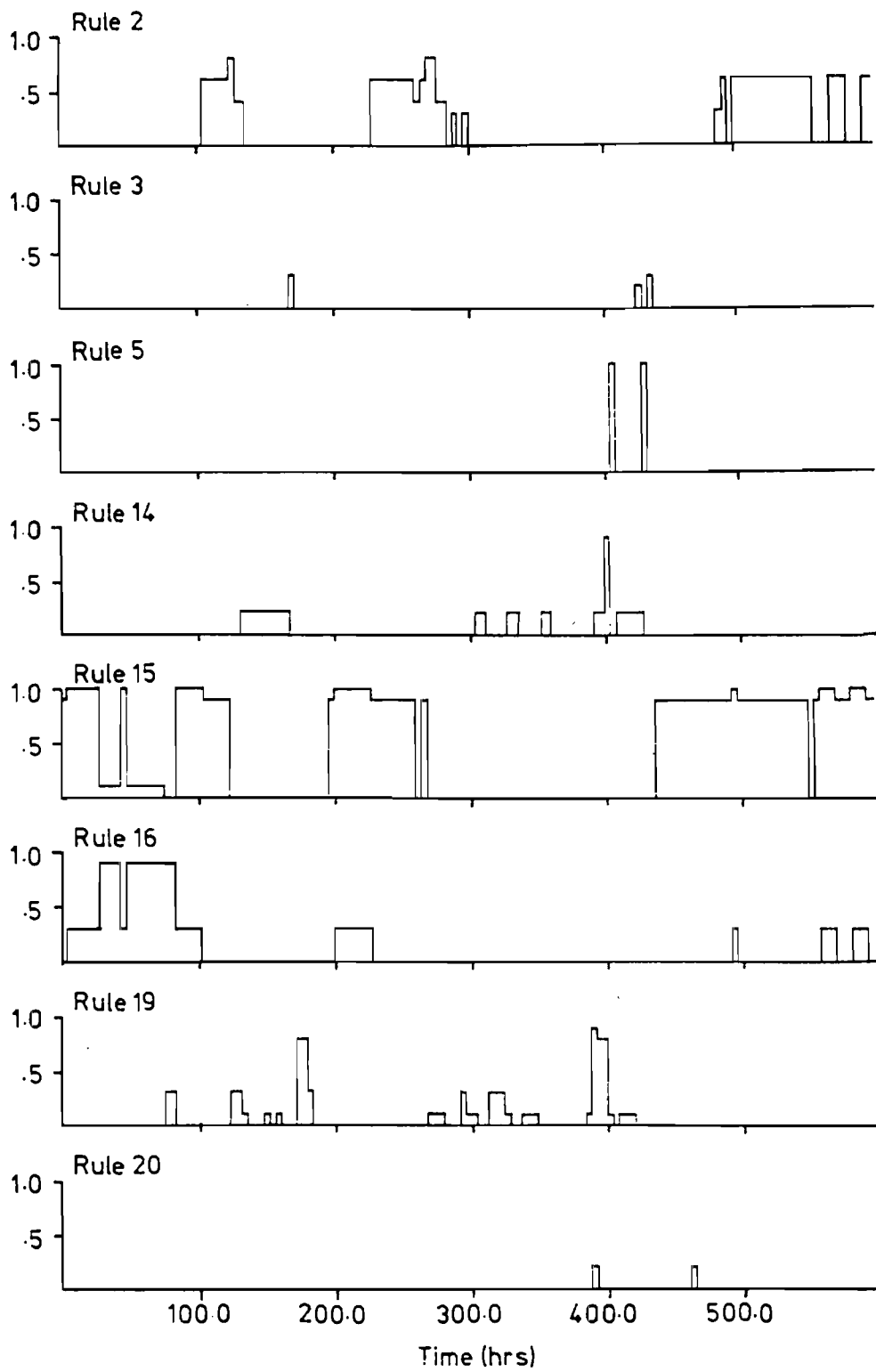


Figure 8. Rule activity chart: II.