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Application of Fuzzy networks for evaluation of Anaerobic Digester performance at the full-scale level

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ABSTRACT: *Due to high organic loads and low energy consumption, anaerobic digestion is Brazil's main route to treating sanitary sewage. However, anaerobic processes are complex and depend on several biochemical reactions promoted by different microorganisms. This work presents the modeling of reactors anaerobic separated physically on real scale based on fuzzy logic. Two fuzzy inference systems (FIS) were developed to predict the efficiency of reactors anaerobic (up-flow anaerobic sludge blanket - UASB). From this prediction, the behavior of the reactors was studied. The results showed that anaerobic reactors behave differently under the same operating conditions. This study has identified situations where the reactors were operating below the expected efficiency. The modeling showed conditions whereboth reactors presented the expected efficiency (70%). Besides, the present work suggests some possible causes and actions from the reactor's efficiency that will help and support the operational team to correctfailures in real-time. The modeling proposed an approach to understanding the anaerobic process in reactors with only fuzzy inference dismissing other complex models found in the literature also indicated for the modeling of UASB reactors.*
KEYWORDS *anaerobic treatment, artificial intelligence, fuzzy, nebulous logic, wastewater treatment.*

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I. INTRODUCTION

Domestic wastewater by anaerobic treatment has gained greater acceptance in the industry due to the development high-rate anaerobic systems, such as the up-flow anaerobic sludge (UASB reactor).Anaerobic digestion has become an increasingly important technology, particularly for high-strength wastewater (Turkdogan-Adynol 2010).UASB reactors are important because they treat a variety of effluents, require less energy than other aerobic treatments, have lower implementationcosts, and need a smaller area to be installed (Dutta et al., 2018). In addition, this technology is expanding, especially in Brazil, due to favorable climatic conditionssuch as high temperaturestypically found in tropical countries.It has been recognized as the third most popular and extensively used sewage treatment technology in Latin America, where Brazil alone is known to have more than 650 full-scale UASBinstallations (Daverey et al., 2019).

Anaerobic processes are susceptible to several parameters (pH, alkalinity, temperature, hydraulic retention times, substrate and biomass concentration, dissolved oxygen, and light intensity) and comprise a variety of reactions, most of which are biochemical and are still subject to intensive research focused on digester design (Lauwers et al., 2013).

Numerous factors hamperthe control of variables in anaerobic processes (García-Diéguez et al., 2011). Among them, it can be highlighted: (1) the non-linear dynamic behavior of the systems; (2) the different levels of complexity inthe existing modules and the irregular change of the parameters, partially influenced by the adaptation of the biomass; (3) disturbances caused by the difference in the flow and organic load at the inlet; and (4) the lack of reliability in the sensors (intracellular sensors)to measure intracellular activities. Classical methods show significant difficulties inautomatically controlling the wastewater treatment processes (Vijayaraghavan, 2015), butsmarter methodologies become fundamental for scenario simulation, fault correction and safe operation.

The performance of the anaerobic process varies significantly due toseveral characteristics and operational conditions (organic loading rates, pH, toxic organic compounds). But several attempts to develop a representative knowledge-based prediction model allow the investigation of the key variables in greater detail (Turkdogan-Adynol 2010). There has been a growing integration between Artificial Intelligence and wastewater treatment processes (Bernadelli 2020).

Fuzzy logic has become a robust technique for modeling wastewater quality and pollution (Nadiri, 2018). Many complex dynamics models can be integrated to predict the system responses to sudden or progressive changes in operating parameters: feedstock flow rate and composition, temperature, inhibition, pH (Appels 2008) or indicate the volumetric organic loading rate (Domnanovich 2003). Several advantages to the use of fuzzy rules, some of them: (a) Wide variety of non-linear relations; (b) relatively simple modules; (c) It can be verbally interpreted, bringing them closer to Artificial Intelligence (AI), and (d) it uses data that other methods could not process, such as knowledge and experience.

Among these methods, a fuzzy logic methodology has been successfully employed in various ecological and environmental applications (Turkdogan-Adynol 2010).Turkdogan-Adynol et al. (2010) used a fuzzy-logic-based model to predict biogas and methane production rates in a pilot-scale mesophilic UASB reactor treating molasses wastewater. Julián Cabanillas et al. (2012) presented a new methodology to assess the risk of water effluents from waste-water treatment plants. Dursun (2016) presented an approach based on Fuzzy to assess wastewater treatment alternatives.

According to the literature, only fuzzy controllers can control some outputs mainly due to their set of rules is based on the acquired knowledge of the wastewater treatment plant (Han et al., 2018; Nadiri et al., 2018; Qiao et al., 2018).

Several studies have introduced different methods for controlling and monitoring wastewater treatment plants (WWTP); however, most of them have not addressed the reactor behavior per se, nor have determined organic load in influent; instead, these studies only focused on instrumentation or effluent violations (Baki 2018; Nadiri et al. 2018). Although there are many works on fault detection methods, e.g., multiparametric programming, principal component analysis (PCA), and fuzzy neural networks, they all rely on the manual selection of relevant input and implementation of domain experts (Mamandipoor 2020).Data Envelopment Analysis (DEA) is another methodology based on a fuzzy approach and indicated to assess the efficiency of Decision-Making Units in many different sectors but requires mathematical knowledge more complex (Sadghpour 2020).

This study presents the development of two Fuzzy Inference Systems (FIS) based onfuzzy logic to predict the behavior of UASB reactors and their efficiency based on organic matter removal.Fuzzy Inference Systems (FIS) to improve the modeling performance is a promising and mathematically suitable approach (Abunama 2021). The modules are specific to the WWTP studied, which has no instrumentation and depends on the whole intervention time of the operation team and can support many decisions where operators cannot be available or capableof suggesting proper solutions for some problems.

II. METHODS

The methodology used for the simulations was based on the implementation of Fuzzy Inference System (FIS) modules making use of the following inputs: total suspended solids (TSS) andchemical oxygen demand (COD). The data set used in the simulations was (influentand effluent) from the Palatinatowastewater treatment plant(Coordinates 22°30'52.7"S 43°10'20.2"W), which mainly treats domestic sewageemploying only UASB reactorswith the same configuration (reactor volume and dimensions). This WWTP is in the city of Petrópolis (state of Rio de Janeiro, Brazil), which has a tropical climate. In addition, one side of the city is surrounded by high mountains, which affects the local climate. Rainfall in Petrópolis is concentrated from October to March (Tavares et al. 2019). According to data from the nearest rainfall station to the treatment plant, the average precipitation was 192 mm (peak precipitation is 401 mm in April) during the sampling period (MSTI 2017).

The sewage treatment plant operates with a flow of 684 m^3 per hour. Haimi (2013) points out some items about the sewage treatment plant operation: working 24 hours a day; this means that decisions are taken all the time, with human intervention, many of them arethe operational routine, some of which are elementary, for example, the washing of a reservoir, while others are more complex, involving many variables, such as the punctual receipt of effluent with different characteristics as usual. The type of treatment used by WWTP is an up-flow anaerobic sludge blanket. The system is composed of two UASB reactors.

Wastewater samples collected from the WWTP (influent and effluent) were stored at4°C andanalyzed according to Standard Methods for the Examination of Water and Wastewater. The monitored parameters were selected considering their relationship with organic matter removal. The analytical data of the treatment plant were chosen considering certain relations with organic removal: Total Suspended Solids (TSS) and Chemical Oxygen Demand (COD).

Fig. 1 presents the stages of modeling.

Step 1 - Input Analysis

- Choice of analytical parameters in lab;
- Choice of dataset;
- Stastistic treatment of dataset (mean, regression and standard deviation).

Step 2 - Fuzzy Inference System (FIS) Definition

- Elaboration of:
- 1 - Operational range of the analytical variables TSS and COD according to the knowledge of the operator and dataset historical;
- 2 - Linguistic variables for each fuzzy subset of each variable;
- 3 - Rules;
- 4 - Determination of FIS parameters (Algorithm type, deffuzification method and pertinence functions type).

Step 3 - FIS Modeling

- Implementation of algorithm.

Step 4 - Output Analysis

- Grouping of combinations of scenarios of efficiency considering the linguistic variables;
- Analysis of combinations of zones according to linguistic variable;
- Validation of models.

Fig. 1. Stages of modeling

Two Fuzzy Inference System (FIS) were elaborated based on fuzzy logic to predict the performance of UASB reactors based on organic matter removal (FIS1a and FIS1b)with their inputs and outputs: Total Suspended Solids influent (TSSi) and effluent (TSSe), Chemical Oxygen Demand influent (CODi) and Chemical Oxygen Demand effluent (CODe) according to Table 1.

Table 1: Inputs and Outputs of FIS Modules

FIS Description	Inputs (mg/L)	Outputs
FIS1a	TSSi; TSSe; CODi; CODe	Reactor 1 - Efficiency (%)
FIS1b	TSSi; TSSe; CODi; CODe	Reactor 2 - Efficiency (%)

The modules were implemented in a fuzzy logic structure, available in the fuzzy logic toolbox of the MATLAB software (V2-14a The Mathworks, Natick, USA), usingdata collected from the full-scale sanitary sewage treatment plant in steady-state operation. The implementation algorithmwas based on Mamdani, using a centroid as a defuzzification method, where the input and output variables were defined by triangular-type pertinence functions.

Zadeh (1965) defined fuzzy logic as a linguistic variable whose values are words or sentences in a natural or synthetic language. In this paper, each parameter of a WWTP is considered as a linguistic variable in the fuzzy sets: ‘Low (L)’, ‘Normal (N)’, and ‘High (H)’ as its linguistic term. The inference rules used in each module were elaborated using provided data for the inference machine containing rules of the “if and then” type. The terms "medium" and "high" were defined as linguistic variables for each fuzzy subset of each variable. The membership functions for each fuzzy subset were defined according to each operational range of the dataset from WWTP and are presented in Table 2.

Table 2: Operational range and linguistic variable of the dataset from WWTP

FIS Description Parameters	Operational range (ppm)- FIS1a and FIS1b	Linguistic variable
TSSi	0-321	Low
	322-550	Normal
	551-799	High
TSSe	0 - 15	Low
	14-30	Normal
	31 - 49	High
CODi	0-300	Low
	301-620	Normal
	621-935	High
CODe	0-27	Low
	28-56	Normal
	57-100	High
Efficiency	20-42	Low
	43-59	Normal
	60-85	High

The rule bases are presented in Appendix A, indicating as low, normal or high operation conditions of the WWTP, according to the operatorknowledge.
The modules FIS1a and FIS1b are presented in Fig.2. According to the output from the model (efficiency),some possible causesare listed in Table 5 to support the manager.

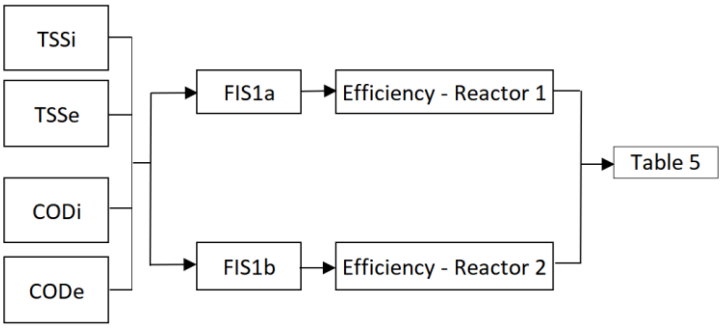

Fig. 2. Schematic of the inference modules (FIS1a and FIS1b)

Each input (TSSi, TSSe, CODi and CODe) has three ranges (low, normal, and high) and the range will be classified as zone 1 (Z1 - low), zone 2 (Z2 - normal) and zone 3 (Z3 - high), respectively. According to fuzzy modeling rules, the composition of these zones will indicate the efficiency of the given reactor.

The response expected using modules 1 and 2 will be the efficiency of reactors, both in (%). In tropical countries, UASB reactors for domestic wastewater are widely used. There are several full-scale plants already in operation in Colombia, Brazil, Indonesia, India, and Egypt, and COD removals expected above 70% are discussed by several authors (Lew 2004).

After the modeling, based on the manager's experience and the reactor's efficiency, some scenarios were obtained to interpret and predict the behavior of the reactors even for the operator with less experience.

III. RESULTS AND DISCUSSION

The analysis obtained through this modeling will allow the operator the process realignment (correction of failure) and the correction of many factors that may decrease efficiency in the treatment plant giving more safety in operation. Decisions (qualitative and quantitative) based on real data have become a challenge for environmental engineers over all stages of the process, from data collection, storage and processing up to analysis and interpretation of the results. Uncertainties accumulate along this chain (Lermontov et al., 2009).

Considering the set of rules and four inputs emerged 70 combinations of scenarios. Table 3 shows the efficiency percentages obtained through the modeling of reactors 1 and 2 only considering only scenarios of 70% and 40% efficiency, both in range according to Table 2 ($20 \leq$ efficiency ≤ 85).

Table 3: Efficiency of the reactor after modeling

Reactor	Inputs Reactors 1 and 2 (in ppm)				Efficiency (%)
	TSSi	TSSe	CODi	CODe	
Reactor 1 - FIS1a	400	23	747	15	70
	651	38	468	15	
	651	8	788	15	
	424	38	468	44	40
Reactor 2 - FIS1b	400	25	802	12	70
	699	40	426	12	
	699	6	788	12	
	400	39	468	44	40

The modeling showed that the TSSe and CODe parameters are critical for the reactors to obtain an expected efficiency to promote pollution reduction. The modeling indicates close to what values these efficiencies are obtained. It is observed that three models showthe efficiency of 70%, while different combinations of these present efficiency below this percentage.Comparing the CODe values of both reactors, it can be observed that small variations in these values already promote a decrease in the efficiency of the reactors.The results indicated that the CODe parameter is much more critical than the TSSe, in both reactors, because the difference between the values is smaller. Therefore, a slight change in operation regarding reactors can lead to low efficiency.

Many scenarios can be obtained through the model. To best understandFig. 2 shows e.g.only 31 rules with inputs for the parameters and their efficiency and values that belong to zone 3 (Z3 – 627 - high), zone 1 (Z1-5 - low), zone 3 (Z3-706 - high), and zone 1 (Z1-12 - low). The efficiency for this combination is 71.1%. These zones will make it easier to draw up the combinations of scenarios.

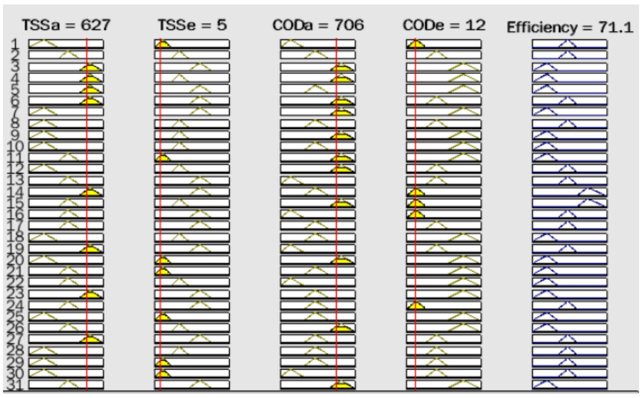

Fig. 2. Membership function plots and Rules Viewer

Table 4 showsthe scenarios that were presented by modeling, where Z1 = low, Z2 = normal and Z3 = high:

Table 4: Combination of scenarios

Scenario	Combination	% Efficiency
1, 2 and 3	Z1Z1Z2Z3, Z1Z1Z3Z3, Z1Z3Z1Z3	31.8
4to14	Z1Z2Z2Z3, Z1Z2Z3Z3, Z2Z1Z2Z3, Z2Z1Z3Z3, Z2Z2Z1Z3, Z2Z2Z2Z3, Z2Z2Z3Z3, Z2Z3Z3Z3, Z3Z2Z3Z3, Z3Z3Z2Z3, Z3Z3Z3Z3	31.9
15	Z2Z3Z2Z2	40.1
16 to 28	Z1Z1Z1Z1, Z1Z1Z1Z2, Z1Z1Z2Z2, Z1Z2Z2Z2, Z1Z2Z3Z2, Z2Z2Z2Z2, Z2Z2Z3Z2, Z2Z3Z1Z1, Z2Z3Z1Z2, Z2Z3Z2Z1, Z3Z3Z1Z2, Z3Z3Z2Z2, Z3Z3Z3Z2	51.1
29 to 67	Z1Z1Z1Z3, Z1Z1Z2Z1, Z1Z1Z3Z1, Z1Z1Z3Z2, Z1Z2Z1Z1, Z1Z2Z1Z2, Z1Z2Z1Z3, Z1Z2Z2Z1, Z1Z2Z3Z1, Z1Z3Z1Z1, Z1Z3Z2Z1, Z1Z3Z2Z2, Z1Z3Z2Z3, Z2Z1Z1Z1, Z2Z1Z1Z2, Z2Z1Z1Z3, Z2Z1Z2Z1, Z2Z1Z2Z2, Z2Z1Z3Z1, Z2Z2Z1Z1, Z2Z2Z1Z2, Z2Z2Z2Z1, Z2Z3Z1Z3, Z2Z3Z2Z3, Z2Z3Z3Z1, Z2Z3Z3Z2, Z3Z1Z1Z1, Z3Z1Z1Z2, Z3Z1Z1Z3, Z3Z1Z2Z1, Z3Z1Z2Z3, Z3Z1Z3Z2, Z3Z1Z3Z3, Z3Z2Z2Z2, Z3Z2Z2Z3, Z3Z2Z3Z1, Z3Z3Z1Z1, Z3Z3Z1Z3, Z3Z3Z3Z1	52.5
68 and 69	Z2Z2Z3Z1, Z3Z3Z2Z1	70.9
70	Z3Z1Z3Z1	71.1

Considering the input dataset, the modeling resulted in only three scenarios with efficiency above 70%. Most of the results indicated efficiency of 51%and 52.5%, which suggest that the reactors may be working with organic loads above those shown.

Fig. 3 shows how the distribution of the number of scenarios and efficiency. The difference between the modeling of reactors 1 and 2 was 0.16%, which means that efficiency rates are very close.

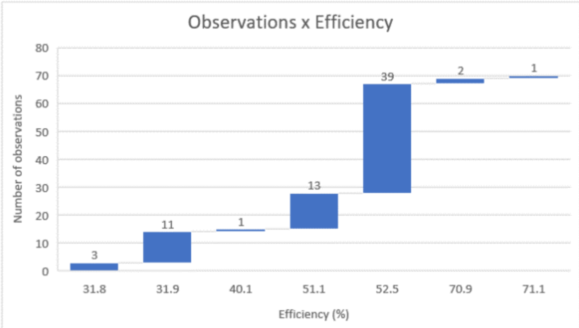

Fig. 3. Distribution of observations andefficiency

After elaborating on the modeling of reactors 1 and 2 (Table 3 and 4), it is suggested according to Table 5, the presentation of the most common faults and their respective corrective actions where sixpossible causes were elaborated from the modeling of FIS1a and FIS1b: High CODi, High TSSe, High TSSi, High TSSe/Possible drag of sludge blanket, High CODi/High TSSi, High CODi/Possible drag of sludge blanket, Normal operation. Through the combined interpretation of these suggested possible causes, the local manager can detect, for example, low methanogenic activity, and the elevation of organic matter, among other scenarios, aiming to anticipate corrections of failures when required.

Table 5: Possible causes and Actions

#	Efficiency (%)	Possible Causes	Actions
1	30-55	High CODi	(1) Check excessive accumulation of scum in the distribution channel; (2) Check the recirculation flow of aerobic sludge from the decanter to the reactor (overtime, promoting the under-dimensioning of the reactor - maximum 50%);
2		High TSSe	(1) Check the incoming flow in the treatment plant; (2) Check the return flow (recirculation) of the sludge through the airlift system, measuring the volume directed to the reactor (solids overload in the UASB);
3		High TSSi	(1) Check the accumulation of sand in the bottom and probable uneven distribution of flow to the reactor distribution boxes; (2) Check excessive accumulation of scum in the distribution channel;
4		High TSSe/Possible drag of sludge blanket	(1) Check the incoming flow in the treatment plant; (2) Check the return flow (recirculation) of the sludge through the airlift system, measuring the volume directed to each reactor (solids overload in the UASB); (3) Check the wastewater flow meter and to verify if the flow is below or on the average. Correct if required;
5		High CODi/High TSSi//Possible drag of sludge blanket	(1) Check excessive accumulation of scum in the distribution channel; (2) Check the recirculation flow of sludge from the decanter to the reactor (overtime, promoting the under-dimensioning of the reactor);
6	70	Normal operation	Expected project removal at 70% for each reactor.

Considering the results presented by the simulated scenarios in Tables 3 and 4, it is possible to identify deficiencies in the reactors. In this scenario, suspended solids can promote an overload in the WWTP's subsequent processes (aerobic reactors).For instance, the possible causes 1 and 5, high organic loads and high concentrations of suspended solids,can affect the efficiency of the whole WWTP. This scenario certainly demandsa set of correcting actions.

Monitoring the anaerobic reactor'sperformance is crucial because it is necessary to produce an effluent pre-treatable to the aerobic reactor, the subsequent step for polishing the effluent (Erdirencelebi 2011). The modules FIS1a and FIS1b presented an efficiency between 30-70%, expected for this technology, butit can be observed that both do not perform withthe same efficiencydespite the operation with the same condition. For this reason, the modeling of reactors 1 and 2 may allow an operation with more safety and the possibility of error correction in real-time.

IV. VALIDATION OF MODEL

For validation, a different dataset of analytical data from the treatment plant was inserted into the models implemented through fuzzy logic. According to the results of the models, they were grouped into three groups: 30-40, 50 and 70% (output ranges obtained from the inputs in the elaboration of the FIS1a and FIS1b models).
The results were compared with efficiency results calculated using a classical methodology (Efficiency = [(In - Out)/In] x 100).
Then, the results were treated using the formulas, according to Table 6, and then compared.

Table 6 – Equations and correction factor

Efficiency (%)	Fuzzy	Classical
30-40	media	((TSSi+CODi)-40)/4
50	media	(TSSi+CODi)/4
70	(TSSi+CODi)/4	((TSSi+CODi)-40)/4

Fig. 4 shows R2 of 0.8636, corroborating a significant correlation between the efficiency results, calculated by the classical methodology and the outputs of the fuzzy model.

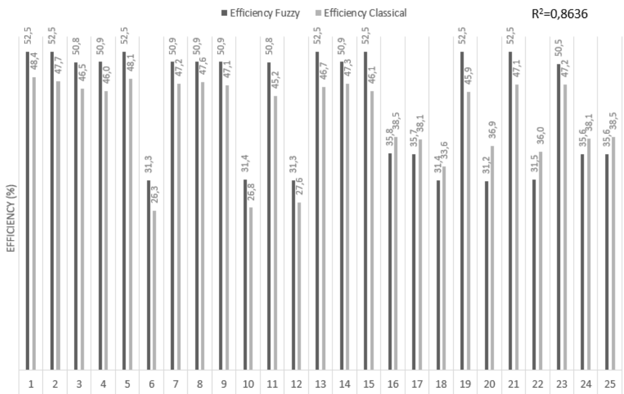

Fig. 4. R squared between predicted vs real values for 25 observations

V. CONCLUSIONS

- The results showed the capacity of the models working with different variables from the wastewater treatment plant to determine the efficiency and possible anomalies in the operation of anaerobic reactors.
- The model could identify which concentrations of COD and TSS the efficiency can be below the expected.
- This study differs from other methodologies because it does not present a combination of different methodologies, e.g., neuro-fuzzy. However, it could predict and support many WWTP decisions besides predicting the reactors'behavior. The results showed how only fuzzy logic could be used to support the manager in many choices in WWTP despite the strong nonlinearity and disturbance of the anaerobic systems.
- If we consider the modeling proposed by many other authors, the models in this study evaluated the use of parameters that offer easy and quick responses at the lab and can predict efficiency.This means a quick dataset to analyze and feed the models.
- Modelslike Benchmark Simulation Model (BSM1 and BSM2) are complex, requiring a high level of specialization (Lauwers 2013).These factors make the model proposed in this paper an intelligent and easy tool for managers in operational routines.

In addition, many models of prediction and control found in the literature refer to pilot-scale stages, and this work contributes with one more model developed on a real scale.

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Appendix A Module Rules

Rules – FIS1a e FIS1b

#	TSSi If	TSSe and	CODi and	CODe and	Efficiency
1	V1=L1	V2=L2	V3=L3	V4=L4	Normal
2	V1=N1	V2=N2	V3=N3	V4=N4	Normal
3	V1=H1	V2=H2	V3=H3	V4=H4	Low
4	V1=H1	V2=N2	V3=H3	V4=H4	Low
5	V1=H1	V2=H2	V3=N3	V4=H4	Low
6	V1=H1	V2=H2	V3=H3	V4=N4	Normal
7	V1=L1	V2=H2	V3=H3	V4=H4	Low
8	V1=L1	V2=N2	V3=N3	V4=N4	Normal
9	V1=L1	V2=N2	V3=H3	V4=H4	Low

10	V1=L1	V2=N2	V3=N3	V4=H4	Low
11	V1=N1	V2=L2	V3=H3	V4=H4	Low
12	V1=L1	V2=N2	V3=H3	V4=N4	Normal
13	V1=N1	V2=H2	V3=L3	V4=N4	Normal
14	V1=H1	V2=H2	V3=N3	V4=L4	High
15	V1=N1	V2=N2	V3=H3	V4=L4	High
16	V1=N1	V2=H2	V3=L3	V4=L4	Normal
17	V1=N1	V2=H2	V3=N3	V4=N4	Normal
18	V1=L1	V2=N2	V3=N3	V4=H4	High
19	V1=H1	V2=H2	V3=L3	V4=N4	Normal
20	V1=L1	V2=L2	V3=H3	V4=H4	Low
21	V1=N1	V2=L2	V3=N3	V4=H4	Low
22	V1=N1	V2=N2	V3=L3	V4=H4	Low
23	V1=H1	V2=H2	V3=N3	V4=H4	Low
24	V1=N1	V2=H2	V3=N3	V4=L4	Normal
25	V1=L1	V2=L2	V3=N3	V4=H4	Low
26	V1=N1	V2=N2	V3=H3	V4=H4	Low
27	V1=H1	V2=H2	V3=N3	V4=N4	Normal
28	V1=L1	V2=N2	V3=N3	V4=N4	Normal
29	V1=L1	V2=L2	V3=N3	V4=N4	Normal
30	V1=L1	V2=L2	V3=L3	V4=N4	Normal
31	V1=N1	V2=H2	V3=H3	V4=H4	Low
32	V1=N1	V2=H2	V3=N3	V4=N4	Low
33	V1=N1	V2=N2	V3=H3	V4=N4	Normal
34	V1=N1	V2=N2	V3=N3	V4=H4	Low
35	V1=H1	V2=L2	V3=H3	V4=L4	High
36	V1=L1	V2=H2	V3=L3	V4=H4	Low
37	V1=H1	V2=N2	V3=H3	V4=N4	Normal