Acoustic Metal Impact Signal Processing with Fuzzy Logic for the Monitoring of Loose Parts in Nuclear Power Plant

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ABSTRACT

This paper proposes a loose part monitoring system (LPMS) design with a signal processing method based on fuzzy logic. Considering fuzzy characteristics of metallic impact waveform due to not only interferences from various types of noises in an operating nuclear power plant but also complex wave propagation paths within a monitored mechanical structure, the proposed LPMS design incorporates the comprehensive relations among impact signal features in the fuzzy rule bases for the purposes of alarm discrimination and impact diagnosis improvement. The impact signal features for the fuzzy rule bases include the rising time, the falling time, and the peak voltage values of the impact signal envelopes. Fuzzy inference results based on the fuzzy membership values of these impact signal features determine the confidence level data for each signal feature. The total integrated confidence level data is used for alarm discrimination and impact diagnosis purposes. Through the perpormance test of the proposed LPMS with mock-up structures and instrumentation facility, test results show that the system is effective in diagnosis of the loose part impact event(i.e., the evaluation of possible impacted area and degree of impact magnitude) as well as in suppressing false alarm generation.

I. Introduction

One of the primary functions for operating and maintaining a nuclear power plant is to monitor and diagnose the mechanical impact event due to free moving objects or loosed parts in the Nuclear Steam Supply System(NSSS) major components[1]. When those loose parts caught in the high velocity flows of the reactor coolant fluid strike against the NSSS components, they can cause signifincant damage. Utilities are becoming increasingly aware that they need reliable Loose Part Monitoring System (LPMS) as operating plants age [2].

Various types of the LPMS have been put to practical use in nuclear power plants since 1978 to meet the licensing requirements of USNRC Regulatory Guide 1.133[1].

A number of techniques have also been suggested to improve the performance of the LPMS. A substantial number of systems have given spurious alarms, have failed to detect actual loose parts, and have lacked diagnostic capability for investigating detected signals. This has resulted in a mistrust of the systems and the loss of potential avoidance of loose part damage[2].

Conventional approaches for the alarm discrimination are generally the logicl synthesis of several discrimination parameters based on the deterministic logic carefully chosen by an operator or designer of the system. However, it is very difficult to accomplish both high sensitivity for the detection of loose-part and suppression for the false alarm generation. Therefore, the ASME standard OMa-S/G-1991 Addenda (Part 12) specifies the maximum alert level as follows regarding the present industry technology level[10]:

"Individual channel threshold levels (setpoint) shall be adjusted after reaching power operation so that the system false alarm rate caused by type 2 false alarms is approximately one event every two weeks."

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Regarding the above statement in the ASME standard recently issued, the suppression of false alarms with conventional techniques seems to be limited to keep the minimum sensitivity of loose part detection. Therefore, new intelligent types of alarm processing techniques are required for the accomplishment of both high sensitivity for the loose-part detection and very low rate of spurious alrms.

After valid signal determination, an estimate should be made of the location, mass, and energy. To perform these diagnosis functions reliably and immediately, the system should be designed with sophisticated signal processing and computer technologies. Some advanced systems recently developed con perform some of these diagnosis functions by using the parameters and/or data analysis for the impact signals in both time and frequency domains [2-5].

This paper shows the design scheme of an intelligent LPMS with the fuzzy logic for both alarm discrimination and diagnosis of loose part event. The loose part detection and diagnosis techniques used in the proposed Fuzzy LPMS are introduced in Section II. Section III deals with the development of the intelligent system using fuzzy logic. In Section IV, performance evaluation of the proposed Fuzzy LPMS is made through experimental test, in the aspect of both alarm discrimination and impact diagnosis capability. Lastly, this study is summarized and concluded with closing remarks in Section V.

II. Detection and Diagnosis of Loose Part

2.1 Detection of Loose Part

Loose part monitoring is based on the analysis of the acoustic noise generated by the mechanical impacts. Mechanical impacts signals can be produced by the collision between a loose part and pressure-vessel wall. This impact signal propagates through the vessel structure and can be detected by the sensors mouned on the outer suface of the monitored-vessel. Accelerometers are generally used for the detection of impact waves. Sensors are strategically located at each natural collection region. Fig. 2-1 shows a typical arrangement of sensors mounted on the outer suface of the major

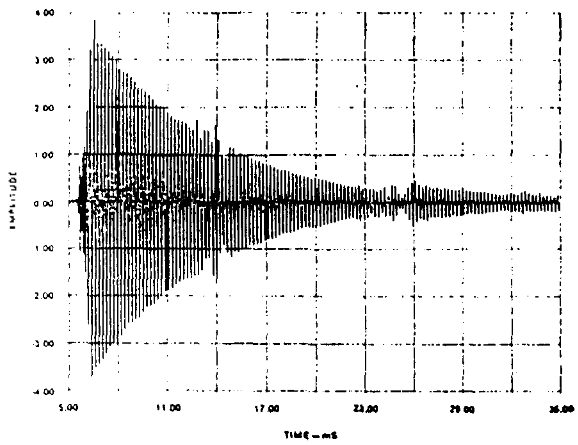


Fig. 2-2. Typical Impact Signal from a Reactor Vessel Sensor

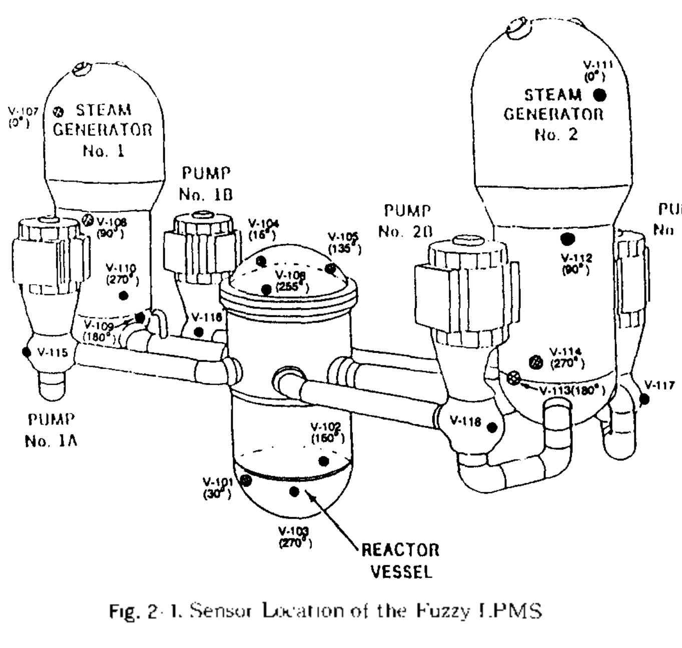


Fig. 2-1. Sensor Location of the Fuzzy LPMS

components in the NSSS in nuclear power plant, where the sensor positions are marked with small black circle.

Typical impact signals caused by loose parts in the reactor vessel can be identified by the burst-type acoustic signals as shown in Fig. 2-2[4]. Fig. 2-3 shows an impact waveform signal and its zoomed waveform from the mock-up steel plate (of 25mm thickness) tested by an impact hammer. An impact force against a metal structure excites an acoustic field that can be described as the combination of a number of wave propagation modes[2]. Hertz impact theory has been used to investigate metal impact properties for loose part monitoring applications. Hertz theory and experimental data show that the dominant wave modes for the loose part impact events are the bending and quasi-longitudinal wave modes. Refer to Fig. 2-4 for the wave modes and plate particle displacement for the longitudinal, shear and bending wave modes[6].

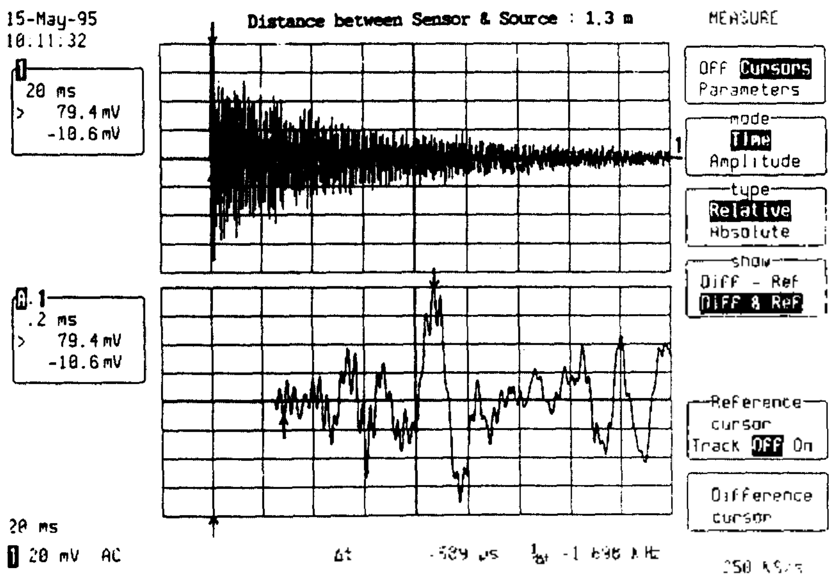


Fig. 2-3. Metal Impact Signal for 25mm Steel Plate

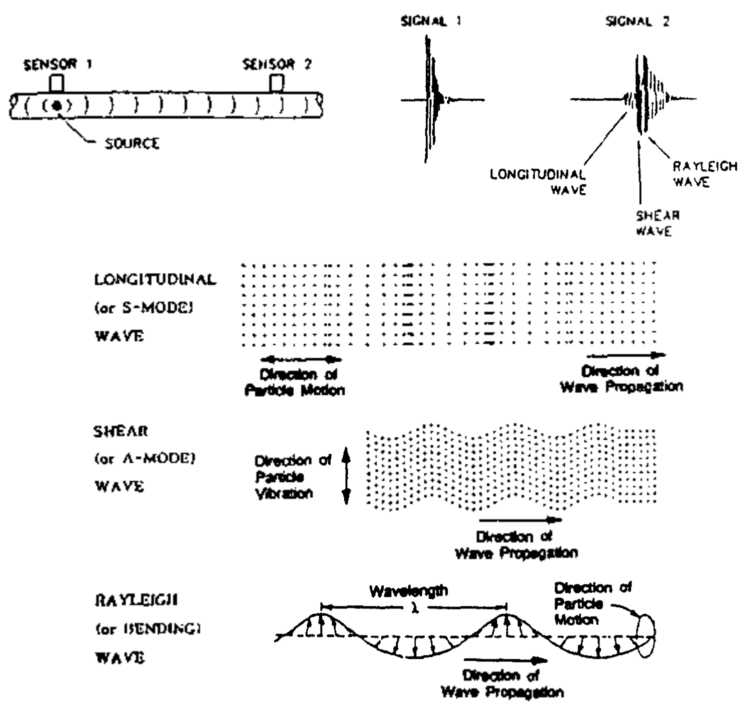


Fig. 2-4. Wave Modes and Plate Particle Displacement

2.2 Diagnosis of Loose Part

After valid signal determination, an estimate should be made of the location, mass, and energy[7]. Determining the impact location is primarily based on the measurement of wave arrival times at different sensor locations. The ability to locate a loose part decreases as the distance to a sensor increases due to dispersion of the wave shape and reduced signal amplitude. Detailed signal analysis is required to obtain good estimates for the impact mass and energy. The wave frequency content is a primary means for estimating mass. The mass information, detected signal amplitude (i.e., acceleration information at sensor location), and known distance between the sensor and impact location permit relatively good estimates of energy for free moving loose parts in monitored collection regions. The mass and energy estimates should also use the LPMS impact calibration data, and include consideration of uncertainty as a function of the estimated impact location and possible impact source[2].

2.2.1 Localization with Arrival Time Method

Impact location can be calculated as the intersection of the hyperbolas using the relative arrival time differences among the impact wave signals from more than three accelerometers. This method can use the arrival time of dominant wave mode signals, i.e. bending wave signals. Therefore, the arrival time method can be used where the background noise level is relatively high compared with impact signals. The impact location can be caluculated by using the group velocity (v_g) of the bending wave mode and arrival time difference data ($\Delta T_{i,j}$) as follows [3] :

$$(r_2-r_1)=v_g\times\Delta T_{1,2}=C_1$$
$$(r_3-r_2)=v_g\times\Delta T_{2,3}=C_2$$

r_i : Distance from Sensor No. i(refer to Fig.2-5).
$\Delta T_{i,j}$: Arrival time difference between Sensor No. i and j.

V_g = 2450 m/ms, PIA = (2.2,2), ATB = (0.22, -0.055, -0.16),
IS = (13.5,8)

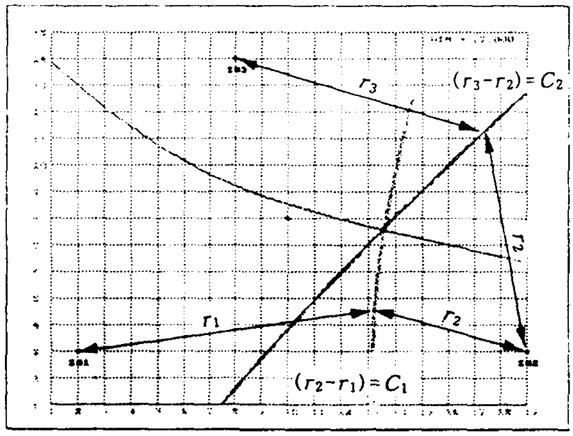


Fig. 2-5. Localization using Arrival Time Method with 3 Sensors

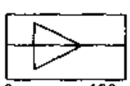
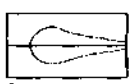
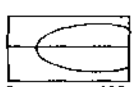
2.2.2 Envelope Curve Characteristics of Impact Signals

The envelope pattern of burst-type impact signals from the sensors around the impact source are varied by the distance between sesor and the impact source. As the distance increases, signal arrival time is delayed, rising time is increased, and falling time is also increased. Table 2-1 shows the relation between the patterns of the impact signal envelope and the various distances from impact source to the sensor mounted on 25mm steel plate.

III. Design of *Fuzzy LPMS*

3.1 Design Concepts of *Fuzzy LPMS*

Table 2-1. Relation between Envelope Patterns and Impact Distance

Distance	0 - 1 m	about 3 m	about 10 m
Patterns of Wave Shape	 0 100ms	 0 100ms	 0 100ms
Characteristics	o Rise sharp and reach the peak within several waves. o Decay relatively fast	o Rise rather slow and require several msec before reach the peak o Decay relatively slow	o Rise very slow and peak point is not clear. o Decay very slow and continue more than 100 msec

Individual measures of signal discrimination parameters are generally not sufficient to determine whether there is a loose part inside the monitored components[2]. Therefore, an adequate combination of several discrimination parameters should be incorporated in the design of alarm discrimination logic. Conventional approaches are based on the crisp synthesis of discrimination parameters and comparison with a fixed or floating alarm setpoint value. The suppression of false alarms with conventional techniques seems to be limited to keep the minimum sensitivity of loose part detection.

For the development of an intelligent LPMS, called the *Fuzzy LPMS*, the fuzzy logic is introduced in this paper for both alarm discrimination and impact diagnosis. By using the fuzzy logic, the comprehensive relations among the impact signal parameters can be incorporated in the alarm discrimination logic in the form of fuzzy rule bases. The fuzzy logic is used to determine a confidence-level of loose part regarding an existence of the true loose parts, and to estimate the possible impacted-area, and the degree of impact magnitude. See Fig. 3-1 for the *Fuzzy LPMS* functional flow chart.

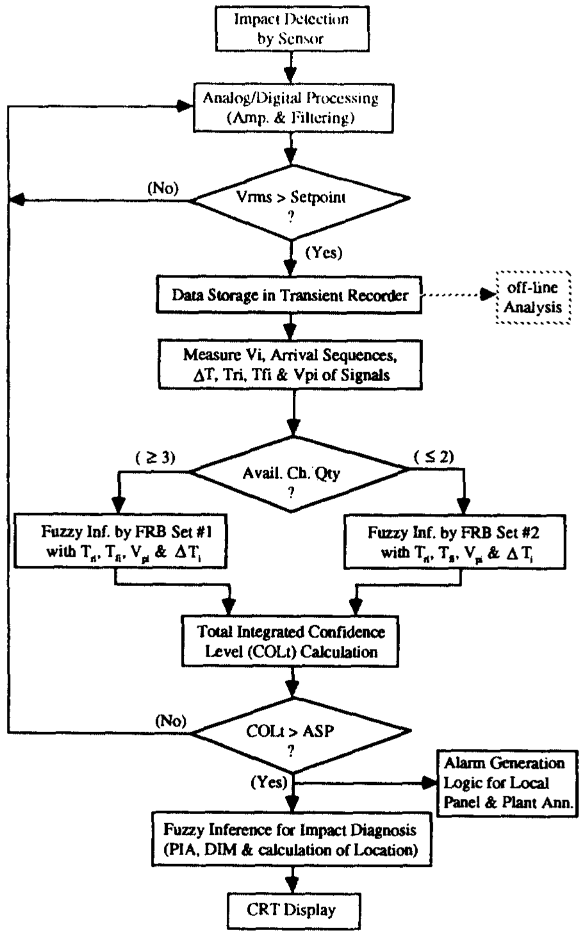


Fig. 3-1. Functional Flowchart of the Fuzzy-LPMS

3.2 Paramenter Characterization for Impact Signals

The parameter characterization was performed to prepare the fuzzy rule bases and membership functions for the impact signal parameters. The impact signal arrival times of *So* and *Ao* mode (T_{So} and T_{Ao}), and their arrival time differences (ΔT_{ij}) were measured using the rectangular type (2 m x 1.

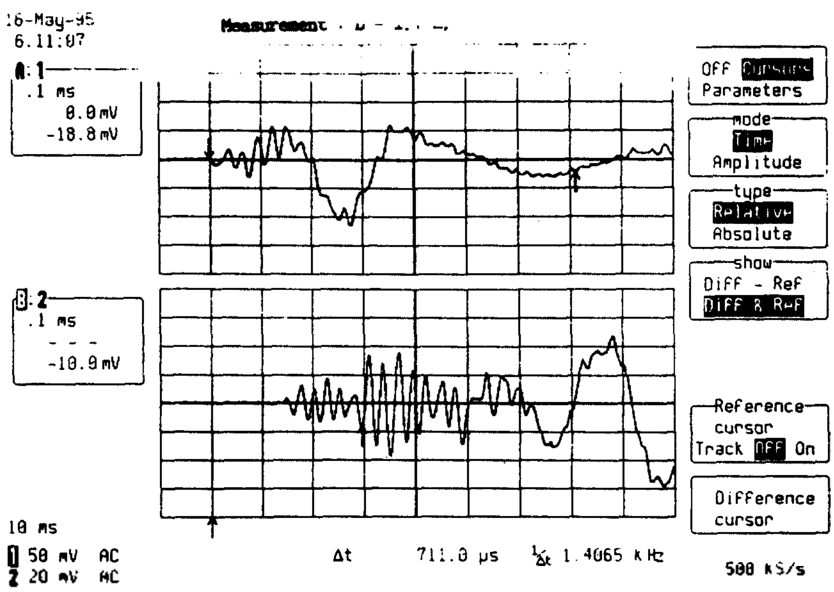


Fig. 3-2. Arrival Time Measurement of Ao Mode Signal

5m, 25mm thickness) mock-up plate. See Fig. 3-2 for the arrival time measurement of Ao mode of impact signals. The figure show the relative time differences between the impact source signal from the accelerometer mounted on impact hammer and the accelerometer signal from the mock-up plate. The rising time (T_r), falling time(T_f) and amplitude decay (V_d) characteristics of the impact signal envelope were also surveyed using the same mock-up plate. The averaged test data are summarized in Table 3-1.

The initial several cycles of dominant Ao mode of impact signals are greatly affected by the contact

Table 3-1. Impact Signal Parameter Characteristics

Dist. (m)	IH Ext.	T_{So} (ms)	V_{So} (m/ms)	T_{Ao} (ms)	V_{Ao} (m/ms)	ΔTT_{A-S} (ms)	Tr (ms)	Tf (ms)	DP_{Ao} (μs)	DF_{Ao} (kHz)	Acc. (g)	Vd (mV)
0.3	w/o	0.09	3.33	0.12	2.50	0.03	0.17	20.5	253	4.0	20.2	198.4
	w/	0.09	3.33	0.13	2.31	0.04	0.21	20.8	284	3.5	20.2	198.4
0.5	w/o	0.14	3.57	0.20	2.50	0.06	0.15	35.6	246	4.1	19.9	175.0
	w/	0.14	3.57	0.20	2.50	0.06	0.24	20.1	246	4.1	19.9	175.0
0.8	w/o	0.23	3.48	0.31	2.58	0.08	0.49	14.6	244	4.1	16.3	159.4
	w/	0.23	3.48	0.32	2.50	0.09	0.50	17.8	255	3.9	15.9	156.3
1.0	w/o	0.31	3.23	0.42	2.38	0.11	0.54	46.1	258	3.9	14.8	145.3
	w/	0.31	3.23	0.41	2.44	0.10	0.56	25.7	284	3.5	14.5	142.2
1.3	w/o	0.41	3.17	0.54	2.41	0.13	0.56	27.5	222	4.5	14.0	137.5
	w/	0.41	3.17	0.54	2.41	0.13	0.58	27.6	225	4.4	13.5	132.8
1.3	w/o	0.46	3.26	0.61	2.46	0.15	1.11	36.5	218	4.6	13.1	128.1
	w/	0.46	3.26	0.61	2.46	0.15	0.97	31.3	256	3.9	12.7	125.0
1.7	w/o	0.54	3.15	0.71	2.39	0.17	1.79	48.9	244	4.1	12.0	117.2
	w/	0.53	3.21	0.70	2.43	0.17	1.60	49.2	276	3.6	12.2	118.8
2.0	w/o	0.62	3.23	0.81	2.47	0.19	0.70	46.4	207	4.8	13.1	128.1
	w/	0.62	3.23	0.81	2.47	0.19	0.67	42.0	221	4.5	12.7	125.0
Aver.	w/o	0.35	3.30	0.47	2.46	0.12	0.69	34.5	236	4.2	15.1	148.6
	w/	0.35	3.31	0.47	2.44	0.12	0.67	29.3	255	3.9	14.9	146.7

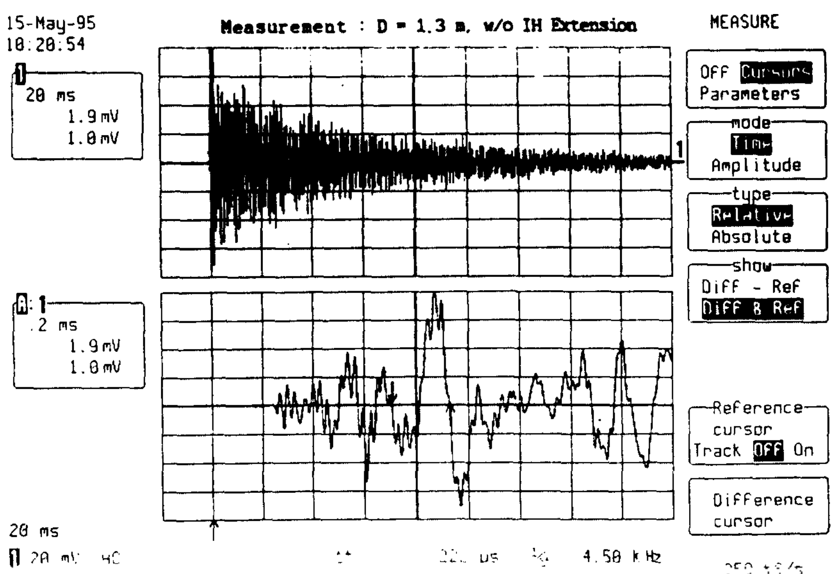


Fig. 3-3. Dominant Period and Frequency of Ao Mode

time between the impacted objects. Therefore, dominant A_0 mode period (DP_{A_0}), which is a period in between dominant peaks of the few cycle after initiation of A_0 mode of the impact signals, were surveyed using the impact hammer and sensors mounted on the rectangular type of mock-up facility. See Fig. 3-3 for the typical case of dominant A_0 mode period and frequency (DP_{A_0} and DF_{A_0}) measurement of the impact signals. The test data for DP_{A_0} and DF_{A_0} in Table 3-1 show that these data these data are not influenced by the distance between the impact source and the monitored sensor. However, the use of impact hammer extender generally affects DP_{A_0} and DF_{A_0} as shown in Table 3-1.

3.3 Fuzzification, Fuzzy Inference and Defuzzification

The Fuzzy logic configuration of the *Fuzzy LPMS* is shown in Fig. 3-4 where the fuzzy logic part consists of fuzzifier, fuzzy the base, fuzzy inference engine, and defuzzifier. The process of classifying a variable using membership functions and degree of membership is called fuzzification. The triangular-type membership function is used for all input and output variables. The shapes of membership functions and the universe of discourse for the variables of rising time, falling time, peak voltage and degree of impact magnitude are shown in Fig. 3-5 through 3-8. Normalized values are used for peak voltages (Vp1 through Vp3) and confidence level data(COL1, through COL3, and COLt).

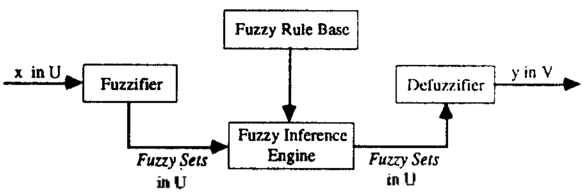


Fig. 3-4. Configuration of Fuzzy Logic Part of the Fuzzy LPMS

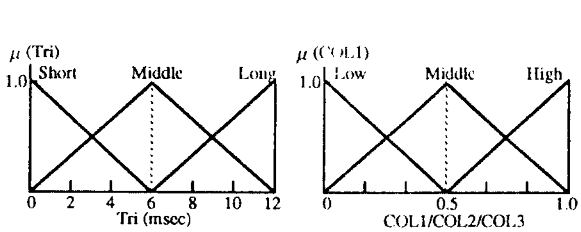


Fig. 3-5. Membership Functions for Tri and COL1/COL2/COL3

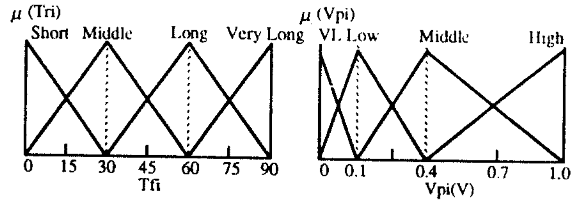


Fig. 3-6. Membership Functions for Tfi and Vpi

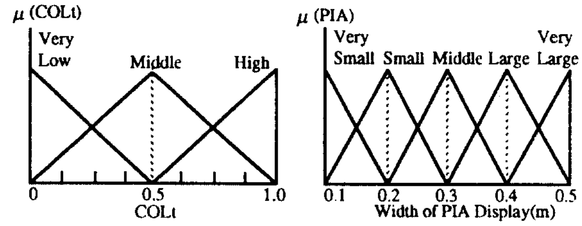


Fig. 3-7. Membership Functions for COLt and PIA

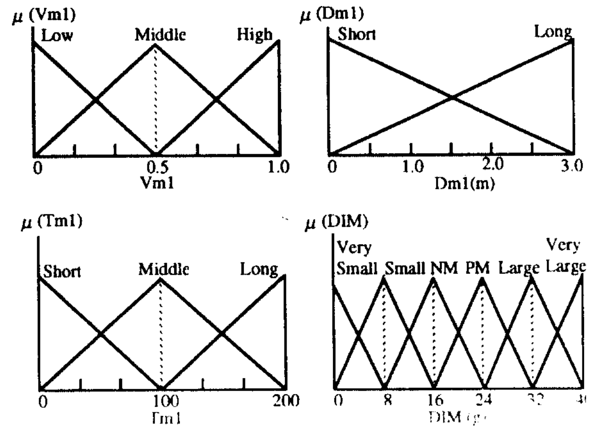


Fig. 3-8. Membership Functions for Vml, Dml, Tml and DIM

For the *Fuzzy LPMS* design, the fuzzy IF-THEN rules are applied by incorporating human expert knowledge with many linguistic input/output variables. The fuzzifier maps crisp points of input to fuzzy sets, and the defuzzifier maps fuzzy sets to crisp points of output. In this study, Fuzzy Logic Development Kit (FULDEK) is used for the performance of fuzzy inference logic for the COL's, PIA and DIM evaluation. The FULDEK is a Windows-based application program which has a simple rule editor and a simulation program[9].

3.4 Design of Alarm Discrimination Part

For the design of alarm discrimination logic, the following discrimination parameters are directly or indirectly considered[8]:

(a) Rising Time of Wave Envelope : directly used

for COL1 evaluation.
(b) Falling Time of Wave Envelope : directly used for COL2 evaluation.
(c) Peak Voltage of Wave : directly used for COL3 evaluation.
(d) Wave Arrival Orders : directly used for the rules of COL1 COL3.
(e) Background Noise : indirectly used for the rules of COL1 COL3.
(f) Sensor Locations : indirectly used for the rules of COL1-COL3.

3.4.1 Confidence Evaluation with at least three channels

As shown in Table 2-1, the rising time of the impact signal envelope is characterized by sharp rise near the impact source location, and slow rise far from the impact source location. The falling time or duration of the impact signal envelope is characterized by rather fast decay near the impact source location, and very slow decay far from the impact source location. The fuzzy rule bases for the evaluation of rising and falling time were made based on the relationship between the wave arrival sequences and envelope pattern changes. Refer to Ref. [8] for the detailed information on the fuzzy rule bases regarding the rising and falling times.

Because metal impact signals have a characteristic attenuation as function of distance, the relative amplitude values of impact signals from adjacent sensors can provide general information about the impact location and energy. Relative signal amplitude changes between sensors in a loose part collection region can also contribute to verify the presence of a loose part that is moving around within that region. Considering impact wave arrival sequences and the wave amplitude values, the fuzzy rule base regarding peak voltage of the impact signals is made as shown in Table 3-2.

3.4.2 Confidence Evaluation with limited input channels

There is a possibility of input channel failure because of sensor degradation or cable disconnection, and less than three input channels are available for a monitoring region. In this case the diagnosis of the metal impact is difficult because the precise impact source localization is not possible. Considering this kind of situation, the *Fuzzy LPMS* has a block of avaiable channel quantity check and a specialized fuzzy rule base (Table 3-3) for the alarm discrimination. Therefore, the *Fuzzy LPMS* is capable of

Table 3-2. Fuzzy Rule Base regarding Peak Voltage

1. If Vp1 is High,	Vp2 is High	& Vp3 is Middle,	then COL1 is High.
2. If Vp1 is High,	Vp2 is Middle	& Vp3 is Middle,	then COL1 is High.
3. If Vp1 is High,	Vp3 is Middle	& Vp3 is Low,	then COL1 is High.
4. If Vp1 is High,	Vp2 is Low	& Vp3 is Low,	then COL1 is High.
5. If Vp1 is Middle,	Vp2 is Middle	& Vp3 is Low,	then COL1 is High.
6. If Vp1 is Middle,	Vp2 is Low	& Vp3 Low,	then COL1 is High.
7. If Vp1 is Low,	Vp2 is Low	& Vp3 is V.Low,	then COL1 is Middle.
8. If Vp1 is Low,	Vp2 is V.Low	& Vp3 is V.Low,	then COL1 is Middle.
9. If Vp1 is High,	Vp2 is High	& Vp3 is High,	then COL1 is Middle.
10. If Vp1 is Middle,	Vp2 is Middle	& Vp3 is Middle,	then COL1 is Middle.
11. If Vp1 is Middle,	Vp2 is High	& Vp3 is Any,	then COL1 is Low.
12. If Vp1 is Any,	Vp2 is Middle	& Vp3 is High,	then COL1 is Low.
13. If Vp1 is Middle,	Vp2 is Any	& Vp3 is High,	then COL1 is Low.
14. If Vp1 is Any,	Vp2 is Low	& Vp3 is Middle,	then COL1 is Low.
15. If Vp1 is Low,	Vp2 is Middle	& Vp3 is Any,	then COL1 is Low.
16. If Vp1 is Low,	Vp2 is Any	& Vp3 is Middle,	then COL1 is Low.
17. If Vp1 is Any,	Vp2 is Low	& Vp3 is High,	then COL1 is Low.
18. If Vp1 is Low,	Vp2 is High	& Vp3 is Any,	then COL1 is Low.
19. If Vp1 is Low,	Vp2 is Any	& Vp3 is High,	then COL1 is Low.
20. If Vp1 is V.Low,	Vp2 is Any	& Vp3 is Any,	then COL1 is Low.

Note : Vp1/Vp2/Vp3 mean the value of envelope peak of the first/second/third arrived signal, respectively

Table 3-3. Fuzzy Rule Base for Limited Available Channels

1. If Tri is Short,	Tfi is Long	& Vpi is High,	then COLi is High.
2. If Tri is Middle,	Tfi is Long	& Vpi is High,	then COLi is High.
3. If Tri is Short,	Tfi is Middle	& Vpi is High,	then COLi is High.
4. If Tri is Short,	Tfi is Long	& Vpi is Middle,	then COLi is High.
5. If Tri is Short,	Tfi is Middle	& Vpi is Middle,	then COLi is Middle.
6. If Tri is Middel,	Tfi is Long	& Vpi is Middle,	then COLi is Middle.
7. If Tri is Middle,	Tfi is Middle	& Vpi is High,	then COLi is Middle.
9. If Tri is Middle,	Tfi is Middle	& Vpi is Middle,	then COLi is Middle.
9. If Tri is Long,	Tfi is Any	& Vpi is Any,	then COLi is Low.

Mote : Tr1/Tr2/Tr3 mean the envelope rising time(30% to peak value) of the first/second/third arrived signal, respectively.

alarm discrimination with limited input channels by inferencing the confidence level of each available input signal regarding rising time, falling time and peak voltage. In this case, the arrival order information is not used. With limited quantity of input channels(i.e., less than 3 channels), the diagnosis capability is limited. However, alarm function can be maintained.

3.5 Design of Impact Diagnosis Part

3.5.1 Impact Source Localization

A limitation for the localization of the impact source is that the limited number of sensor should be utilized for the cost effectiveness. For the display of impact source location, two kind of localization methods, including the wave mode method and the arrival time method, are both applied for the *Fuzzy LPMS*. The arrival time method has an advantage of noise-tolerant property especially when the background noise level is high.

3.5.2 Possible Impacted-Area(PIA)

A point-type indication of the impact source location for the loose part event has limited meaning, and it is not practical for the system operation especially when the impact source display with circles or hyperbolas indicates more than one intersection point, or no intersection point at all, because of various noise sources of the plant in operation, and the measurement error for the impact signal parameter characterization.

The PIA display is a unique feature of the *Fuzzy LPMS* design. The *Fuzzy LPMS* is designed to dispaly the PIA based on the relation among Vp1(peak voltage of the first arrived signal) and COLt(total integrated confidence level of input signals) as shown in Table 3-4. The impact source localization software of the *Fuzzy LPMS* is used to draw the hyperbolas (in the arrival time-difference method), and the PIA values are used to adjust the width of hyperbolas to indicate the sectors of possible impact source. The most possible impact source location is considered to be the most multiple overlapped sector of the display. The width of the PIA is increased as the value of COLt decreases, because the larger area should be suspected as a PIA when the lower confident signals are received (refer to Fig. 4-1 and 4-2). Considering both impact signal discrimination capability and uncertainty of each discrimination parameter measurement, the COLt is calculated by simply averaging the input confidence level data.

3.5.3 Degree of Impact Magnitude (DIM)

The DIM is evaluated, in this study, based on the

Table 3-4. Fuzzy Rule Base for the PIA

1. If COLt is High,	& Vpi is High,	then PIA is Very Small.
2. If COLt is High,	& Vpi is Middle,	then PIA is Very Small.
3. If COLt is High,	& Vpi is Low,	then PIA is Small.
4. If COLt is Middle,	& Vpi is High,	then PIA is Middle.
5. If COLt is Middle,	& Vpi is Middle,	then PIA is Middle.
6. If COLt is Middle,	& Vpi is Low,	then PIA is Large.
7. If COLt is Low,	& Vpi is Any,	then PIA is Large.

Table 3-5. Fuzzy Rule Base regarding DIM

1. If Vm1 is High,	Dm1 is Long	&	Tm1 is Long,	then DIM is Very Large.
2. If Vm1 is High,	Dm1 is Long	&	Tm1 is Middle,	then DIM is Large.
3. If Vm1 is High,	Dm1 is Short	&	Tm1 is Long,	then DIM is Large.
4. If Vm1 is High,	Dm1 is Short	&	Tm1 is Middle,	then DIM is P.Middle.
5. If Vm1 is Middle,	Dm1 is Long	&	Tm1 is Long,	then DIM is P.Middle.
6. If Vm1 is Middle,	Dm1 is Long	&	Tm1 is Middle,	then DIM is N.Middle.
7. If Vm1 is Middle,	Dm1 is Long	&	Tm1 is Short,	then DIM is N.Middle.
8. If Vm1 is Middle,	Dm1 is Short	&	Tm1 is Long,	then DIM is N.Middle.
9. If Vm1 is Middle,	Dm1 is Short	&	Tm1 is Middle,	then DIM is Small.
10. If Vm1 is Middle,	Dm1 is Short	&	Tm1 is Any,	then DIM is Small.
11. If Vm1 is Low,	Dm1 is Long	&	Tm1 is Middle,	then DIM is Small.
12. If Vm1 is Low,	Dm1 is Long	&	Tm1 is Short,	then DIM is Very Small.
13. If Vm1 is Low,	Dm1 is Short	&	Tm1 is Any,	then DIM is Very Small.

Notes : 1. Vp1, Dm1 and Tm1 mean the value of envelope peak, distance between the impact source and sensor, and period of Ao mode of the first arrived signal, respectively
2. P.Middle and N.Middle means Positive Middle and Negative Middle, respectively.

fuzzy rule base considering the relation among the peak voltage of the first arrived signal, the distance between the impact source and the nearest sensor, and the period of the dominant wave mode signal as shown in Table 3-5. The peak voltages of the first arrived signals are used to consider the acceleration magnitude inpacted at the plate. The distances between the impact source and the nearest sensor are used to compensate the attenuation of the impact signal with the increase of distance between an impact source and a sensor. The period of the dominant wave mode signal provides the information closely related with the impact contact time between the impacted plate and a loose-part. The impact event with heavy part is characterized by long period of dominant mode signals, and high DIM values. The DIM values in the unit of gravity acceleration, are displayed in the upper side of the PIA display as shown in Fig. 4-1 and 4-2.

Ⅳ. Experimental Results

4.1 Performance Test of the *Fuzzy LPMS*

The performance test of the detection and diagnosis capability was done by using the mock-up test structures and instrumentation facilities. Performance evaluation of the proposed system was done for the typical ten cases of input data selected for the verification of alarm discrimination and impact diagnosis capability as follows(see Table 4-1) :

(a) Case 1-4 : Input data to test various loose part events around natural collection region of loose parts.

(b) Case 5 : Input data to test the impact occurring far from natural collection region.

(c) Cases 6 & 7 : Input data to test common mode(i. e., EMI) noise, such as high frequency noise in Case 6, and low frequency noise in Case 7.

(d) Case 8-10 : Input data to test various random noise events.

4.2 Alarm Discrimination Capability

For the alarm discrimination purpose, the *Fuzzy LPMS* uses the total integrated confidence data (COLt) by comparing it with a alarm setpoint predetermined by the system designer. Three parameter specific confidence data (COL1 thru COL3) and a total integrated confidence data are compared for each input data case. The result can be summarized as follows(refer to Table 4-1) :

(a) Cases 1-3 : Between High and Middle range of the total integrated confidence data, which are more than 0.7, are found.

(b) Case 4 : COL2 value is relatively small, but COL1 is in middle range and COL3 is very high. Therefore, the COLt value of this case(i.e., 0.66) is found in upper middle range.

(c) Cases 5-10 : At least one of parameter specific confidence data is very small. Therefore, the total integrated confidence data is relatively small(less than 0.4).

Based on the above performance test results, each COL data shows its capability to assess the parameter specific confidence level of input, and the total integrated confidence data (COLt) shows that it can be used as a alarm discrimination index for the impact signals caused by loose-part. The alarm discrimination setpoint in the range between 0.45 and 0.55 of the COLt seems to be conservative based on the performance test results.

4.3 Impact Diagnosis Capability

The PIA and DIM displays are shown in Fig. 4-1 and 4-2, using hyperbola intersections of the arrival time-difference method. The curves drawn on these figures are based on the measured time-difference data among the different input channel signals.

Fig. 4-1 is the case of high confidence level of input data, and the figure shows relatively small overlapped sectors by the hyperbola from three sensors, compared to the ones in Fig. 4-2. The tripple overlapped sectors are considered to be the most possible impacted-areas in both Fig. 4-1 and 4-2.

Fig. 4-1 and 4-2 also show that the DIM values in 'g' unit of acceleration are also displayed along with the PIA display. Fig. 4-3 is a typical example of time-difference measurement between channels No. 1 and No. 3 input signals. In this case, the measured arrival time difference of $\Delta T_{3,1}$ is -0.16 ms. Minus ($-$) sign is required because the A_0 mode arrival time of channel No. 3 is earlier than one of channel No. 1. A diagnosis function to evaluate the mass of the impacted loose-part should be added in further study to complete the diagnosis of the impacted loose part force.

Fig. 4-4 shows the result of impact test which uses the impact source localization software of the arrival time method. In this figure the fuzzy logic is not utilized for the impact source localization, and the figure clearly indicate an intersection point of (9.0, 2.6) approximately. However, the impact source indication if Fig. 4-4 have the error of 9 cm approximately, because the actual impacted-point by the impact hammer during the test is the point of(9.0, 3.5). Without utilizing the PIA method, the error of the impact source display increases as the fuzziness of the input signals increases. Because of the various types of noise and measurement error inevitably related with the LPMS, the result of the impact source localization cannot be focused always on a point.

Fig. 4-5 shows the result of impact test which uses the impact source localization and fuzzy logic software for the indication of possible impacted area (PIA). In this figure, the PIA is considered the area of tripple overlapped by the three strips. The *Fuzzy LPMS* display in Fig. 4-4 shows the PIA of 0.04 m^2 approximately, and the PIA includes the actual impacted point of (9.0, 3.5). Therefore, Fig. 4-5 shows that the PIA display correctly provides a suspected area information of the impact source. The size of PIA increases as the fuzziness of the input signals increase to compensate the localization error corre-

Vg = 2450 m/s, PIA = (12, 12, 12), ATD = (0.22, -0.055, -0.16), IS = (13, 5, 8)

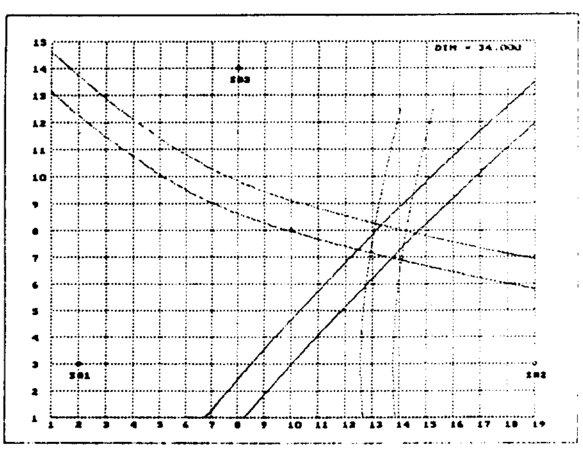


Fig. 4-1. PIA&DIM display for the high confidence level input case

Vg = 2450 m/s, PIA = (27, 27, 27), ATD = (0.16, -0.09, -0.15), IS = (13, 5, 8)

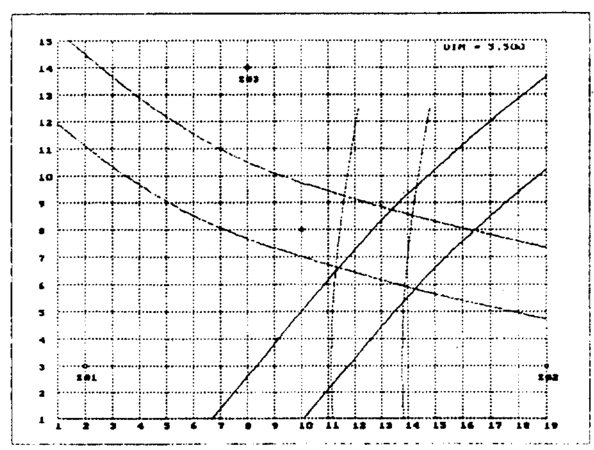


Fig. 4-2. PIA&DIM display for the low confidence level input case

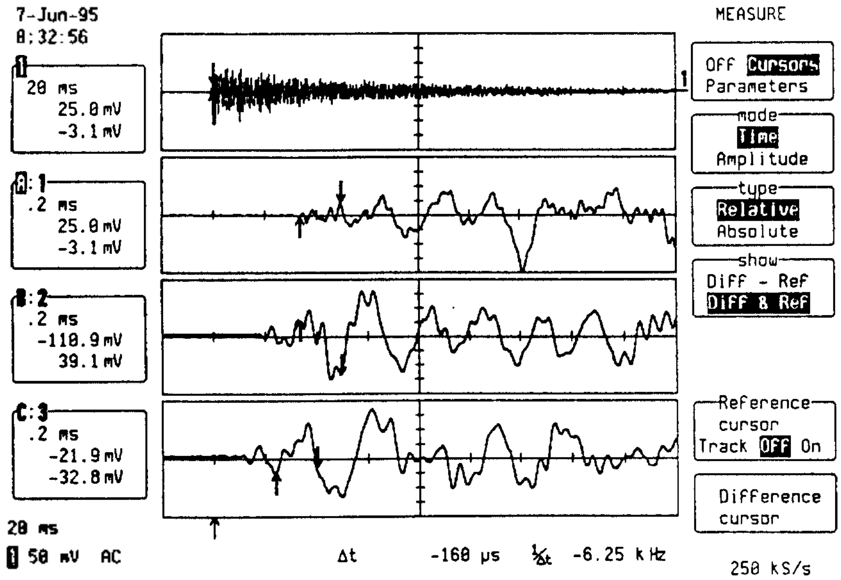


Fig. 4-3. Measurement Case of Arrival Time Difference (ΔT_{ij})

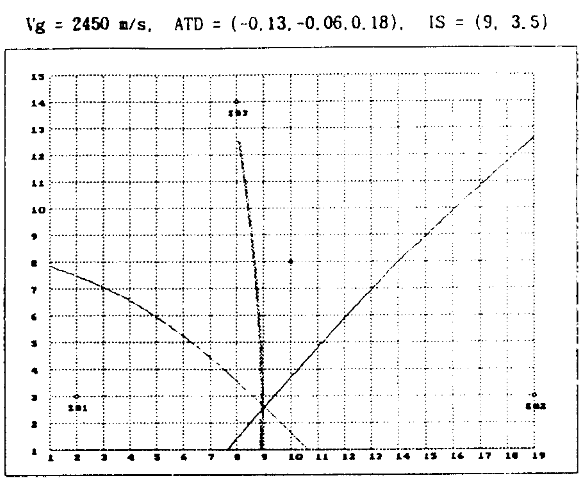


Fig. 4-4. Impact Source Localization display without Fuzzy Logic

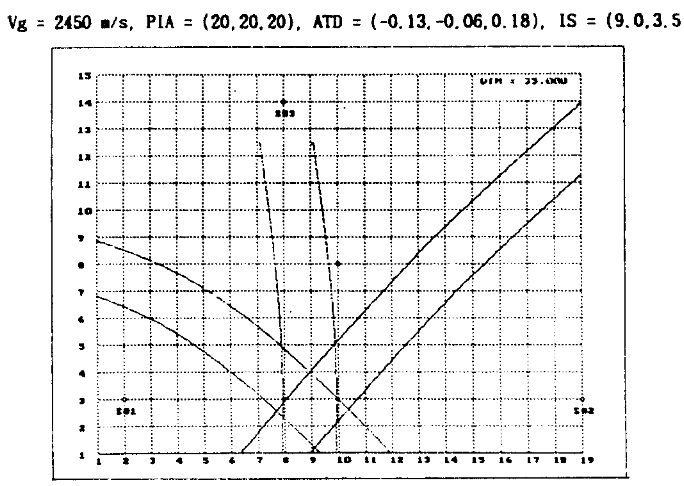


Fig. 4-5. IS Localization and PIA display with Fuzzy Logic

sponding to the uncertainty of the calculation.

In accordance with the test results in Table 4 1, the alarm discrimination setpoint of COLt for the *Fuzzy LPMS* should be in the range between 0.45 and 0.55. In this case, the PIA display will be an intersection of strip like patterns with a width of less than 0.3 m. The more multiple overlapped sector is considered to have the higher possibility of impact source location.

V. Conclusion

In this paper, a loose parts monitoring system with a new signal processing technique using fuzzy logic is proposed. The fuzzy logic is applied for the alarm discrimination and impact diagnosis for the proposed system. In the *Fuzzy LPMS* design, comprehensive relations among the impact signal features are taken into account in the fuzzy rule bases for the intelligent alarm discrimination and impact diagnosis. For the alarm discrimination purpose, the *Fuzzy LPMS* uses

Table 4-1. Performance Test Result of the Fuzzy LPMS

No.	Input (Tri)			O.P.	Input (Tfi)			O.P.	Input (Vpi)			O.P.	Input			Integrated Output		
																Alarm	Diagnosis	
	Tr1	Tr2	Tr3	COL1	Tf1	Tf2	Tf3	COL2	Vp1	Vp2	Vp3	COL3	Vm1	Dm1	Tm1	COLt	PIA	DIM
# 1	Short (1.8)	Short (2.5)	Mid. (4.0)	0.64	Mid. (30.0)	Mid. (45.0)	Long (60.0)	0.99	High (1.0)	High (0.8)	High (0.5)	0.81	High (1.0)	Short (1.3)	Long (190)	0.81	0.12	34.0
# 2	Short (2.0)	Mid. (4.0)	Mid. (6.0)	0.80	Mid. (36.0)	Long (60.0)	Long (69.0)	0.67	Low. (.15)	Low. (.10)	V.L. (.05)	0.63	Mid. (.15)	Short (1.5)	Short (10)	0.70	0.27	5.5
# 3	Short (2.5)	Mid. (5.0)	Mid. (8.0)	0.80	Long (51.0)	Long (60.0)	Long (66.0)	0.54	High (0.8)	Mid. (0.5)	Mid. (0.4)	0.75	High (0.8)	Long (1.7)	Long (200)	0.70	0.17	29.0
# 4	Mid. (4.0)	Mid. (7.0)	Long (8.0)	0.67	Long (57.0)	Long (66.0)	Long (72.0)	0.31	Mid. (0.4)	Low (0.2)	Low (0.1)	0.99	Mid. (0.4)	Long (2.5)	Mid. (120)	0.66	0.24	13.6
# 5	Mid. (7.0)	Long (11.0)	Long (11.0)	0.07	Long (65.0)	Long (72.0)	V.Long (84.0)	0.06	Low. (0.1)	V.L. (.05)	V.L. (.05)	0.50	Mid. (0.1)	Long (2.9)	Short (20)	0.21	0.50	5.7
# 6	Short (2.0)	Short (1.0)	Short (2.0)	0.58	Short (6.0)	Short (3.0)	Short (6.0)	0.02	High (0.9)	High (1.0)	High (0.8)	0.50	High (0.9)	Short (0.1)	Mid. (90)	0.37	0.37	20.0
# 7	Long (11.0)	Long (11.0)	Long (11.0)	0.05	V.Long (75.0)	V.Long (84.0)	V.Long (90.0)	0.00	Mid. (0.3)	Mid. (0.4)	Mid. (0.3)	0.40	Mid. (0.3)	Long (3.0)	Mid. (120)	0.15	0.50	14.7
# 8	Long (11.0)	Mid. (6.0)	Short (2.0)	0.07	Long (60.0)	Mid. (30.0)	Short (6.0)	0.00	Low (0.1)	Mid. (0.5)	High (0.8)	0.50	Low (0.1)	Long (2.7)	Mid. (110)	0.19	0.50	10.0
# 9	Mid. (4.0)	Mid. (6.0)	Short (1.5)	0.36	Long (60.0)	Short (12.0)	Mid. (30.0)	0.00	Mid. (0.5)	High (0.9)	Low (0.2)	0.45	Mid. (0.5)	Long (2.7)	Mid. (110)	0.27	0.46	16.9
#10	Mid. (7.0)	Short (1.0)	Short (2.0)	0.30	Mid. (24.0)	Short (3.0)	Mid. (30.0)	0.04	Mid. (0.5)	Mid. (0.4)	Mid. (0.3)	0.75	Mid. (0.5)	Short (1.0)	Mid. (60)	0.36	0.40	11.2

the total integrated confidence level data (COLt) by comparing it with a alarm setpoint pre-determined by the system designer. The major impact diagnosis functions of the proposed system are the display of possible impacted area and degree of impact magnitude.

The proposed approach to the LPMS design has been revealed to be effective not only in suppressing false alarm generation as described in Section 4.2, but also in characterizing the loose part event, i.e., the PIA and DIM, through the performance tests with a mock-up facility. The PIA display of the *Fuzzy LPMS* has the merit of impact source localization capability, even in the cases of processing noise-contaminated fuzzy input signals by varying the multiple overlapped sector size rather than displaying only curves and intersection points.

Without use of fuzzy logic, the impact localization error has been found in the range of ±10 cm. With the fuzzy logic application in the *Fuzzy LPMS*, the impact localization error could be overcome because the error range is within the PIA sector range. Refer to Fig. 4-4 and 4-5. The impact diagnosis capability of the *Fuzzy LPMS* is analyzed in Section 4.3.

We can finally mention that the fuzzy logic can be generally used for the mechanical impact monitoring and diagnosis of a complex plant structure when the characteristics of the impact wave propagation can be systematically expressed with fuzzy linguistic variables. However, the mechanical property of impact wave propagation depends on the plate thickness and internal structures of the monitored component. Therefore, to apply the proposed *Fuzzy LPMS* to the actual plant facility, the rule bases and membership functions of input and output variables are need to be optimized on each monitoring region.

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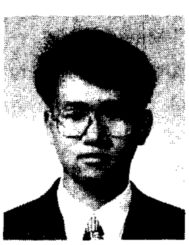

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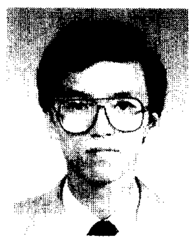

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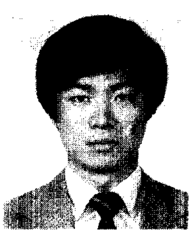

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