Decision Support System Based on Cargo Sensor Information for Liquid Carrier Tanker

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Abstract – In this paper we constructed the Decision Support System (DSS) for liquid cargo tankers based on the International Ship Management Code (ISM Code). To make this system, we first organized a base of expert knowledge concerning liquid tanker operations that largely affect ocean accidents. Based on this expert knowledge, we constructed the decision support system that provides a code of conduct for operating cargo tanks safely. The proposed decision support system could eliminate human error when confronting dangerous situations, so the system will help sailors to operate cargo tanks safely.

Keywords: decision support system, fuzzy, sensor, monitoring system

1. Introduction

A liquid cargo carrier is a sea born structure and thus it can be isolated area from land. Consequently, ships face many kinds of ocean-based dangers. Errors are made when operating ships that lead to accidents in which lives are lost, the environment destroyed, and a great deal of direct and indirect damage is caused to marine transportation enterprises[1].

To prevent ocean accidents, the International Maritime Organization (IMO) has developed many conventions concerning the hardware of vessels such as Safety Of Life At Sea (SOLAS) and prevention of MArine POLlution from ship (MARPOL). These conventions play an important role in preventing accidents at sea. However, they cannot prevent accidents caused by human error. To prevent these accidents, IMO they developed the ISM Code, and it has been in effect since June 1, 1998. Although over 55% of ship operators have used the ISM Code system for over two years, only 24.2% ship operators understand the ISM Code system. Since using the ISM Code system, most operators (about 96.7%) have reported feeling overloaded[2]. Consequently, this system needs to be improved, so we need to improve this system and ISM code-based DDS for liquid cargo carriers has been developed.

In this research, the rules were constructed using the ISM Code, and the fuzzy memberships for sensor inputs use the expert knowledge base for DSS[3]. We used a modified fuzzy inference system for users to support

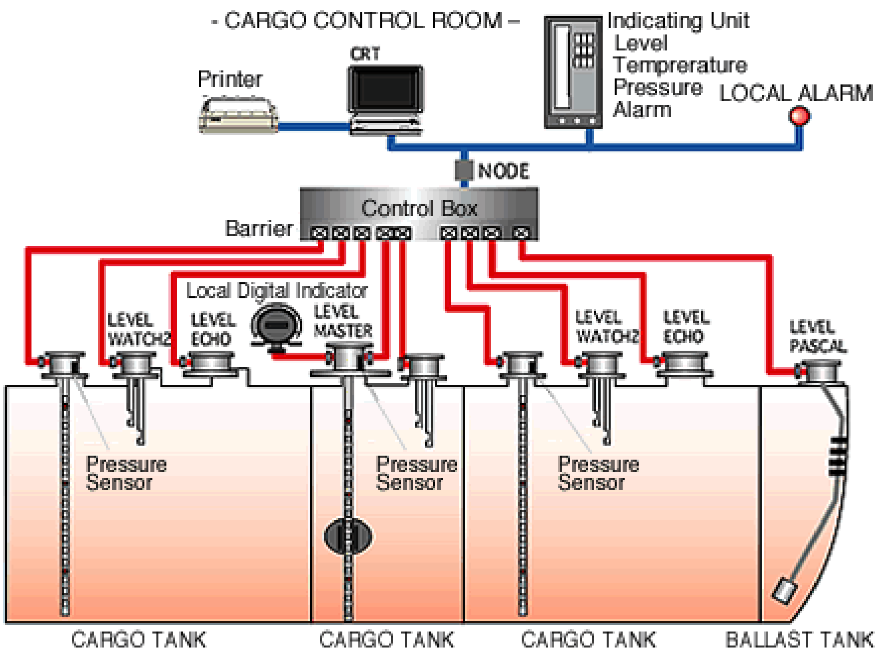

Fig. 1. Cargo monitoring system for liquid carrier takers.

decisions and to prioritize decisions in emergency situations at sea.

2. Monitoring system for liquid cargo carriers

A typical cargo monitoring system is shown in Figure 1. Each tank has six sensors (pressure, level, VOCs, oxygen, temperature, and high overfill sensor) for monitoring. The signal from each sensor is received by the monitoring system in the Cargo Control Room (CCR) where the value of each sensor is displayed. If a sensor defects a danger, then the system alerts the operators. Table 1 shows the characteristics of these sensors.

Table 1. Specification of six sensors for cargo tank.

Sensor	Output	Measurement target	min/Max	Normal range
Level sensor	4-20mA	Height	0/30 *m*	0 - 30
Temp. sensor	4-20mA	Temp.	0/100 ℃	0 - 60
Pressure sensor	4-20mA	Pressure	-0.35/0.5 *bar*	0.07 - 0.2
Oxigen sensor	4-20mA	Oxigen	0-21%	0 - 8
VOCs sensor	4-20mA	Hydro-carbon	0-100%	%<1.2, %>7.2
High overfill sensor	On/Off	Tank overfill	-	Under 95%

3. DSS based on expert's knowledge

We propose the DSS. The DSS imitates experiments of expert and can make decisions from combinative information of six sensors[4]. Our proposed system is explained by algorithm flowchart in Figure 2.

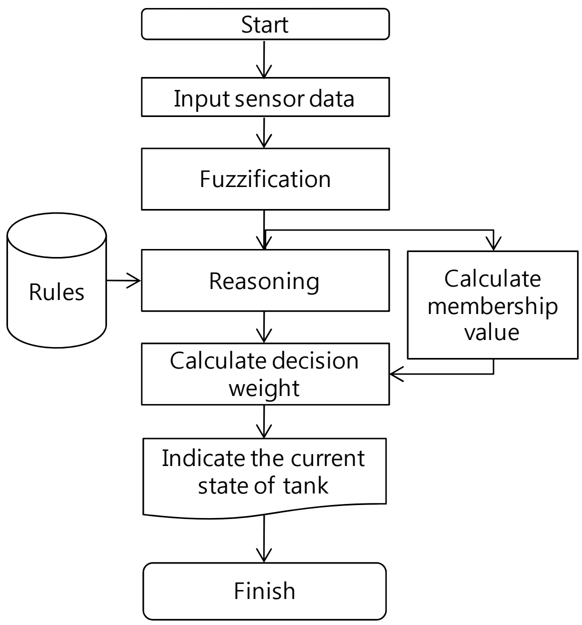

Fig. 2 Decision support system of professional knowledge based.

3.1 Fuzzy inference theory for DSS

This section introduces the fuzzy inference system. First, we introduce fuzzification of input variables for inference. Next, the method for developing the rules is introduced. And last, we will demonstrate the inference method for DSS.

3.1.1 Fuzzification

The fuzzification stage makes fuzzy memberships for sensor inputs and these memberships are used for linguistic variables for fuzzy inference. Generally, linguistic variables describe membership values that are either 0 or 1 in the fuzzy logic. Each sensor has a different input range and characteristics. Consequently, the number of linguistic variables differs for each sensor. In addition, the membership function is used for sensor input. The trapezoidal membership function is used for the two edge ranges and the triangle membership function for the center range. These ranges were determined through expert consultation. Figure 3 shows the constructed fuzzy memberships for each sensor.

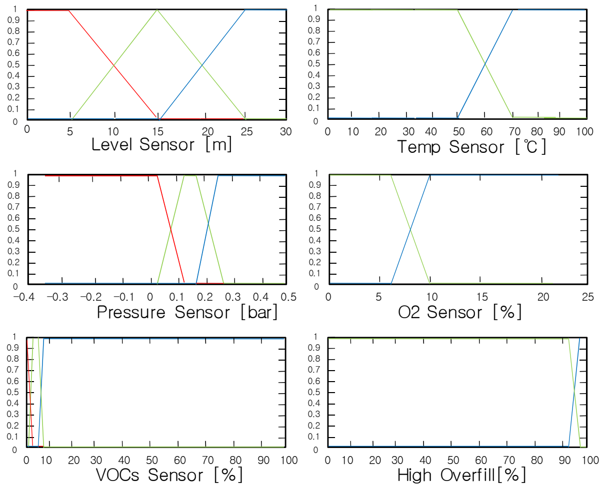

Fig. 3. Fuzzy memberships of six sensors.

3.1.2 Rule extraction

Table 2 shows the eight actions available when using DSS. These actions depend on the monitored cargo conditions. Generally, if an a abnormal condition is indicated by the sensors, then the ISM code can be used to determine an appropriate response. The ISM Code for a liquid cargo tanker consists of 223 combinations of the six sensors. Table 3 shows four combinations from the ISM Codes as examples.

Table 2. Eight actions to do in the navigation of the liquid cargo tanker.

ACTIONS	
1	Normal state
2	Cooling System
3	Upper Pressures Valve
4	Level Measuring or Sounding or HighOverfill Alarm
5	Cargo Cargo Pump Stop
6	Vapour Gas return
7	Inert Gas Injection
8	Low Pressure Valve

We extract 46 rules from the 223 ISM Codes by the heuristic-method. The 'don't care' elements in the ISM

Code were rejected, and we could reduce the 46 rules. Each rule has six combinational sensor inputs and 1 to 4 actions. These rules and operations are showed in Table 4 and 5.

Table 3. ISM code (4/223).

sensors	state N	state L	state H	
Level Sensor	■			Normal state
Temp Sensor	■			
Pressure Sensor	■			
O2 Sensor	■			
VOCs Sensor	■			
High Overfill	■			

kind of sensors	state N	state L	state H	
Level Sensor	■			Cooling System
Temp Sensor			■	
Pressure Sensor	■			
O2 Sensor	■			
VOCs Sensor	■			
High Overfill	■			

kind of sensors	state N	state L	state H	
Level Sensor	■			Upper Pressures Valve
Temp Sensor	■			
Pressure Sensor		■		
O2 Sensor	■			
VOCs Sensor	■			
High Overfill	■			

kind of sensors	state N	state L	state H	
Level Sensor	■			Operating liquefier
Temp Sensor		■		
Pressure Sensor	■			
O2 Sensor	■			
VOCs Sensor	■			
High Overfill	■			

Table 4. Sensor information of rules (4/46).

No	Level	Temp	Pressure	O2	VOCs	Overfill
1	don't care	Normal	Normal	Normal	Normal	Normal
			…			
9	don't care	High	High	Normal	Normal	Normal
			…			
25	High	High	High	Normal	Normal	Low
			…			
46	N/L	Normal	H/N	Normal	High	Low

Table 5. Operations of each rule (4/46).

No	Subject 1	Subject 2	Subject 3	Subject 4
1	Normal condition			
		…		
9	Operate cooling system	Operate upper pressures valve		
		…		
25	Operate cooling system	Operate upper pressures valve	Check level sensor	
		…		
46	Operate cooling system	Cargo pump stop	Vapour gas return	Inert gas injection

3.1.3 Fuzzy inference

In our research, we introduce the fuzzy inference system for the linguistic DSS. It is some different with traditional fuzzy inference systems in output stage. The proposed system deals linguistic terms for output and calculate the priority rate of output instead of the defuzzification calculation of output.

3.14 Calculation of the priority rate for decisions

If the DSS presents over two decisions, it needs priorities to do them. For this, the proposed system is included the calculation algorithm to serve the priorities. The calculation of priority rates are differently calculated by each condition of outputs. And those are listed below:

① The system presents one decision and all input membership values are 1.

② The system presents one decision and more than one input membership values are less than 1.

③ The system presents more than one decisions and more than one input membership values are less than 1.

The ① is very simple case. All sensor inputs have 1 membership values those are certain value for decision and this case has one decision. In this case, priority rate are meaningless and this system does not calculate priority rate.

In the case ②, It has one decision and more than one sensors have two membership values. We explain the calculation of priority rate for this case in Figure 4. The result, "Low Pressure Valve," was inferred from the pressure sensor value by the inference rules. In this case, the system made one decision from the pressure sensor, which had a membership value normalized factor of 0.7 the priority rate of 1 was determined by equation (1). Actually, this case the priority rate does not need to be calculated because ② always has priority rate of 1.

The other hand, case ③ has at a minimum one sensor with two membership values. From these inputs, our system infers several decisions and also calculates the priority rate. We explain Figure 5 shows these procedures with one example. In this example, pressure sensor has a value of 0.2, which is a large (L) membership, and a normalized value of 0.8 (N) also has two values from its two memberships. From these sensor values, DSS infers four results from the rules and infers three decisions: "lower pressure value", "return vapour gas", and "normal condition". Then, three decisions are obtained, and the priority rate of each decision is calculated. First the normalized factor was calculated from equation (1) and the priority rate for each decision was calculated using equation (2). "Return vapor gas" decision has the highest priority rate, 0.69, "lower pressure value" is 0.17, and "normal" decision is 0.14. Two decisions are returned "return vapour gas" and "lower pressure valve" from the pressure sensor and the VOC_sensor values. The DSS system strongly suggested that vapor gas be returned and that the low pressure valve be checked.

4. The DSS tool and Experiments

In this research, we developed the DSS tool using our proposed algorithm. We used Matlab 7.1 to develop DSS. This tool consists of three panels. The "Input" panel shows values measured by each sensor. These measured values are mapped from fuzzy membership values and these membership values are shown in the "Fuzzy Value" panel. The "Output" panel shows the eight decisions and their priority rate. We tested our proposed

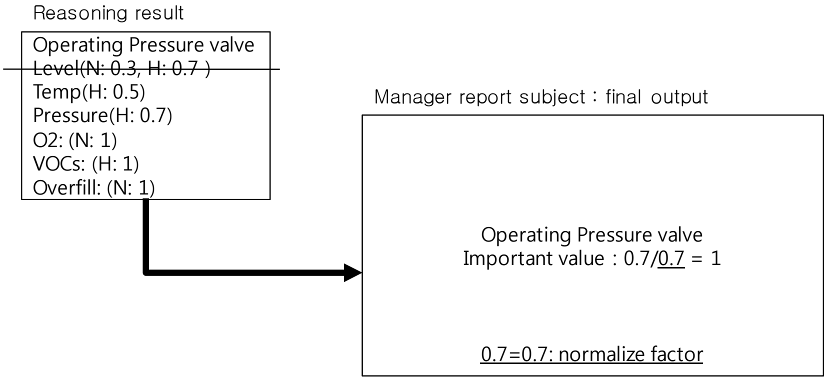

Fig. 4. Calculation of priority rate of decisions(case②).

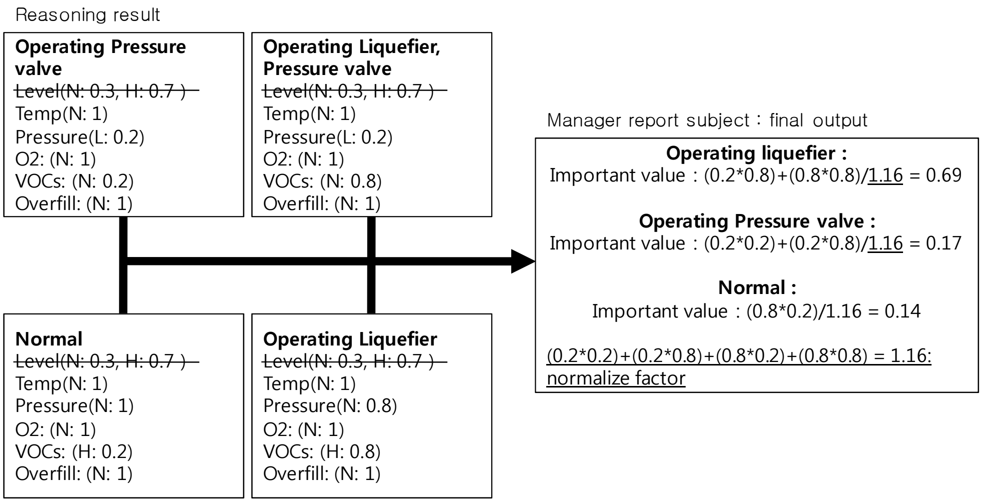

Fig. 5. Calculation of priority rate of decisions(case③).

tool using recorded sensor values from a liquid cargo tanker. These sensor values were used by the DSS tool, and the inferred decisions were compared with the actual tank conditions. In the first situation, the level sensor indicates 15m (cargo height: 30m) and the high overfill sensor detects overfill. However, these results are contradictory. Actually this cargo tanker had a level sensor fault. The DSS tool returned "Check the overfill sensor and the level sensor", which is shown in Figure 6.

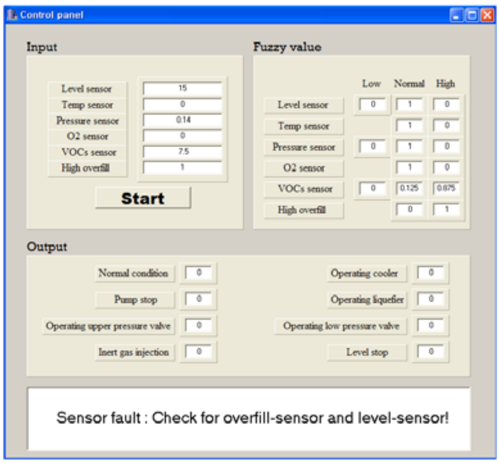

Fig. 6. Detection of sensor fault.

5. Conclusions

We constructed a DSS algorithm and developed a DSS tool for the operation of liquid cargo tankers. The tool provides a code of conduct for the safe operation of cargo tanks. It can help to simplify the operation of a cargo tanker. The proposed DSS tool could decrease the danger of human error, so the system will help sailors in operating cargo tanks more safely.

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