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INTELLIGENT IDENTIFICATION OF FIRES IN SHIP COMPARTMENTS USING A BAYESIAN NETWORK

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Key words: ship compartment fire, Bayesian network, intelligent identification, decision support, fire size, fire type.

ABSTRACT

Fire is always a severe threat to ship safety and survival. To prevent the spread of a fire and eliminate serious accidental consequences, it is imperative for commanders to promptly identify the size and type of the fire so as to take rapid and effective firefighting action. In this study, the architectural design of an advanced ship fire identification system (SFIS) is presented that makes timely and critical decision support for selecting suitable suppression methods and firefighting tactics. Based on a Bayesian network (BN), a novel intelligent identification model that is capable of identifying small, medium or large fires and distinguishing between a solid fire and a fuel oil fire is proposed. The results indicate the effectiveness of the proposed model as well as its robustness during the failure of one fire sensor. The model can be integrated into damage control systems (DCSS) to further enhance the situational awareness of the damage and assist commanders in prompt decision-making by allocating the most efficient firefighting equipment and crew.

I. INTRODUCTION

Fire is one of the most challenging dangers aboard ships (DiNenno et al., 2011). Approximately 15% of marine accidents are shipboard fires (Zhu et al., 2008). The development of new types of container ships, very large crude carriers (VLCC), liquefied natural gas (LNG) carriers, liquefied petroleum gas (LPG) carriers, floating production storage and offloading (FPSO) carriers and warships changed shipboard tonnage, thus requiring different fuel types and quantities. Many combustible materials, including dangerous goods, oil products and engine fuel oil, are stored in various ship areas such as cargo compartments, oil tanks, engine rooms, pump rooms and hangars. When a fire occurs, due to the extreme hazard to the entire ship, it is important to close and seal individual ship compartments, so the heat does not increase rapidly and the smoke does not easily spread. Once out of control, a fire may cause serious injuries to crew or damage to vital ship systems (David, 1998).

To prevent further spread of fire and eliminate serious accidental consequences, a commander must select the most suitable suppression methods and use the most efficient firefighting tactics. However, suppression methods and firefighting tactics mainly depend on the size and type of fire. The stage to which fires develop has a direct impact on the selection of firefighting equipment. The type of combustible determines the extinguishing material selection.

In ships, damage control systems (DCSS) are designed to detect, control and eliminate damage caused by fire. The objective of DCSS is to make timely and critical decisions for the shipboard crew and equipment use scenarios (Calabrese et al., 2012). Two problems in the field of DCSS intelligence are addressed below. Currently, identifying the size and type of a fire typically depends on human investigative reports, which take more time and are fairly inaccurate. Furthermore, fire sensors are known to be unreliable during major crisis when fire or anti-ship weapons are involved, so decision-making regarding fire recognition involves reasoning with conditions of uncertainty and incomplete information about the fire state.

Extensive studies have been conducted on early fire detection on board ships and warships, particularly research on multi-sensor data fusion (Milke and McAvoy, 1995, 1999), early warning fire detection systems (Rose-pehrsson et al., 2000, 2003; Kuo and Chang, 2003), video image fire detection systems (Steinhurst et al., 2003; Gottuk et al., 2006; Owrutsky et al., 2006) and volume sensors (Gottuk and Harrison, 2003; Rose-pehrsson et al., 2006). However, little attention has been devoted to research on fire recognition. Williams et al. (2000) established blackboard models of situational awareness based on volume sensors to accurately detect different damaged types such as fire, smoke and flooding. Minor and Johnson (2007) developed the volume sensor prototype (VSP) systems generally performed better than video image detectors and spot-type smoke detection systems relative to range of detection capabilities, which has the ability to detect fires and reject nuisance

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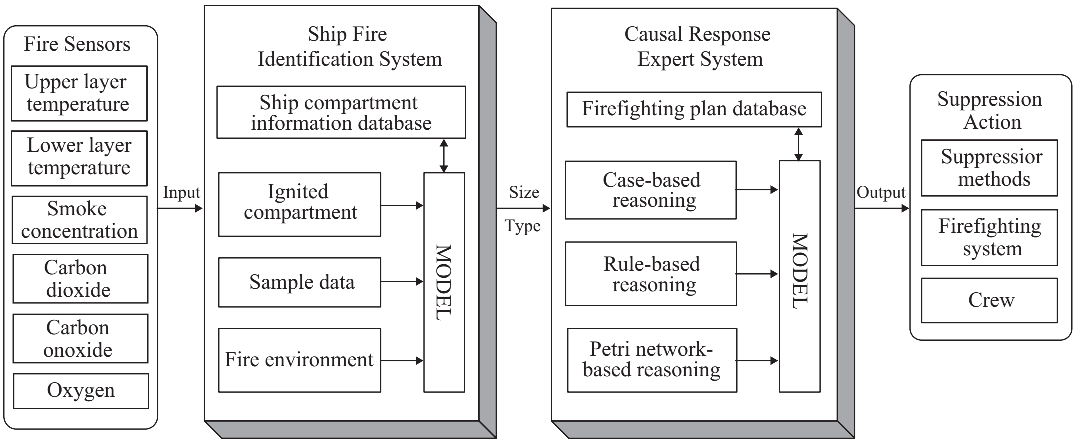


Fig. 1. Architectural design of ship fire identification system.

sources. Zhuang and Li (2009) and Li (2010) studied an incipient fire classification model using least squares wavelet support vector machine (LS-WSVM), but the model is only applicable to several solid materials. Sun et al. (2010) proposed fire identification arithmetic for naked fire, smoldering fire and disturbing fire on composite of rough set support vector machine (RS-SVM). Zhao (2015) studied a fire recognition algorithm based on fuzzy neural network to distinguish the probabilities of naked fire, smoldering fire and no fire. Kim (2015) developed a real-time probabilistic method for identifying fire, smoke, their thermal reflections, and other objects in infrared images. The above methods just discussed naked fire, smoldering fire and no fire, not including the study on distinguishing the size and type of typical ship compartment.

It is assumed that intelligent fire sensors are more advanced than sensors that currently exist on ships; thus, an intelligent ship fire identification system (SFIS) is presented that can be integrated into DCSS designed for the decision support of firefighting actions. Based on a Bayesian network (BN), a powerful tool for reasoning under uncertainty, a novel identification model is established systematically. The effectiveness of the model is evaluated and validated by sample and experimental data. SFIS can provide timely and informed decision support for the allocating firefighting equipment and crew.

The remainder of this paper is organized as follows: Section 2 analyzes the architectural design and system flow of SFIS. Section 3 describes the basis and advantage of BN. In Section 4, based on BN theory and fire development mechanisms, an intelligent shipboard fire identification model for distinguishing the sizes and types of fires is established. Section 5 evaluates the trained model by sample data and validates the BN identification model by experimental data. In section 6, integrated and disintegrated sensor data are compared to demonstrate the robustness of the model. Section 7 presents the conclusions and directions for future research.

II. INTELLIGENT IDENTIFICATION FRAMEWORKS

As analyzed in Section 1, the decision-making task of fire recognition is time critical and involves reasoning under uncertainty. SFIS is designed to provide answers to these key questions. To streamline the decision flow and action execution, five major requirements are identified to drive the design of the SFIS. These requirements include the following:

(1) Monitoring fire status at any time;
(2) Distinguishing the development stage of a fire;
(3) Identifying the type of fuel;
(4) Saving time to allow effective firefighting plans for the determined size and type of fire;
(5) Providing decision support for efficient suppression methods and suitable firefighting equipment and crew.

Fig. 1 shows overall architectural flow of SFIS and its relationship with detection system, causal response expert system (CRES) and suppression action. First, the detection system based on advanced sensors automatically acquires physical and chemical variables of a compartment fire. Next, after the position and corresponding fire environment of the ignited compartment are determined by the compartment database, SFIS intelligently identifies the size and type of the fire by an identification model and predetermined sample data. Then, CRES produces a timely and suitable firefighting plan by reasoning with case-based, ruled-based and petri network-based models. Finally, DCSS assists the commander to choose effective suppression methods and activating efficient firefighting systems and crew to contain, control and eliminate the fire effects. Throughout the four steps, DCSS makes critical decisions related to the fire concerning what to detect, how to identify the fire, how to obtain firefighting plans for suppression, and what actions to be taken to eliminate the fire.

The general SFIS architecture comprises advanced fire sensors, intelligent identification model and decision support plan. As an indispensible part of DCSS, SFIS can effectively identify the development stage of fire and the type of combustible. Furthermore, SFIS provides decision support for the CRES to take efficient firefighting actions.

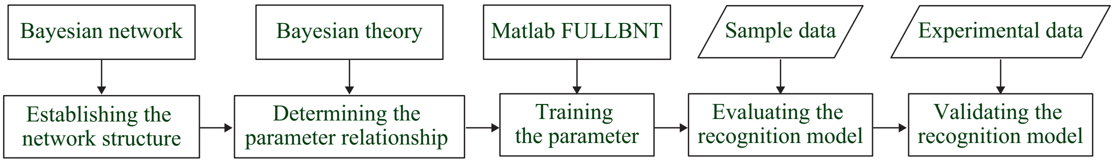


Fig. 2. Overall establishment flow of identification model of shipboard fires.

Advanced fire sensors may be damaged by fires or anti-ship weapons, so disintegrated sensor data are sometimes used to identify compartment fire. A BN has the advantage of dealing with uncertain reasoning with incomplete information, so it can be applied to establish an intelligent identification model to distinguish the size and type of fire automatically. The SFIS will assist commanders to make critical decisions in case of fire accidents by indicating the most suitable firefighting tactics and allocating the most efficient firefighting equipment.

III. FUNDAMENTALS OF BAYESIAN NETWORK

A Bayesian network (BN) is referred to as a directed acyclic graph (DAG), in which the nodes represent variables and are connected by directed arcs that signify dependency or causal relationship between the connected nodes (Baksh et al., 2015). A BN is a framework for reasoning under uncertainty, which ensures high accuracy and robustness (Trucco et al., 2008). With the characteristic of structural calculations and probability propagation based on causality and subjective judgment, a BN is widely used for representing uncertain knowledge (Zhang et al., 2013).

A standard BN with a mathematical symbol can be expressed as

$$B = (S, P) = (V, L, P) \tag{1}$$

where S represents the variable field, $V=\{V_1, V_2, \ldots, V_n\}$ containing n limited variables V_i denotes a set of stochastic variables, $L = \{V_iV_j \mid V_i, V_j \in V\}$ denotes the set of directed lines and $P = \{p(V_i|V_1, V_2, \ldots, V_{i-1}, V_i \in V)\}$ represents the conditional probability distribution.

Suppose that E is the subset of V, conditional probability can be exactly calculated with the given evidence of $E = e$ by

$$p(V_i{=}v_i|E{=}\mathrm{e}) = \frac{p(V_i{=}v_i, E{=}\mathrm{e})}{p(E{=}\mathrm{e})} \tag{2}$$

IV. MODEL ESTABLISHMENTS

As the core of SFIS, The identification model of shipboard fires is established by BN theory and fire development mechanisms.

As shown in Fig. 2, the overall establishment flow of the identification model involves five steps. These steps include the following:

(1) Establishing network structure based on BN;
(2) Determining the relationship of the parameters based on Bayesian theory;
(3) Training the model parameters by the Matlab toolbox, FULLBNT;
(4) Evaluating the identification model by simulated sample data generated by a two-zone fire computer program called the Consolidated Model of Fire and Smoke Transport (CFAST);
(5) Validating the identification model by full-scale fire experimental data from the US Naval Research Laboratory.

1. Establishment of Topological Structure

During the changes in fire development stages, physical and chemical characteristics of different types of fuels make a difference in heat quantity, gas temperature, smoke release rate, flame size, combustion products, light, sound etc. The energy released from a fire may be large, and the smoke and gas species are indispensible factors also associated with the fire. Light obscuration is affected by smoke concentration, which reduces the visibility of the crew. Crew tenability and HRR are mainly determined by the oxygen (O_2) content in the compartment air. The toxicity of the combustion products of carbon monoxide (CO) and carbon dioxide (CO_2) have obvious effects on the crew wellbeing. O_2 concentration, CO concentration, CO_2 concentration and light obscuration are selected in this study as fire identification signals. Moreover, gas temperature are divided into the upper layer temperature (upper temperature) and the lower layer temperature (lower temperature). Temperature sensors, gas sensors and optical density sensors are considered as advanced onboard fire sensors.

Based on the physical and chemical characteristics of different types of fuels during the fire development stage, the topological structure of the recognition model is illustrated in Fig. 3.

The input variables of the model include upper temperature, lower temperature, CO concentration, CO_2 concentration, O_2 concentration and optical density. The output variables of the model are fire size and type. Fire size is divided into three states that represent small, medium and large fires. Fire types include solid and fuel oil fires.

2. Parameter Relationship Determination

When the input and output variables of the model are determined by topological structure, random variables set are obtained by

$$V = \{T_{\mathrm{U}}, T_{\mathrm{L}}, C_{\mathrm{CO}}, C_{\mathrm{CO_2}}, C_{\mathrm{O_2}}, D_0, S_{\mathrm{F}}, C_{\mathrm{F}}\} \tag{3}$$

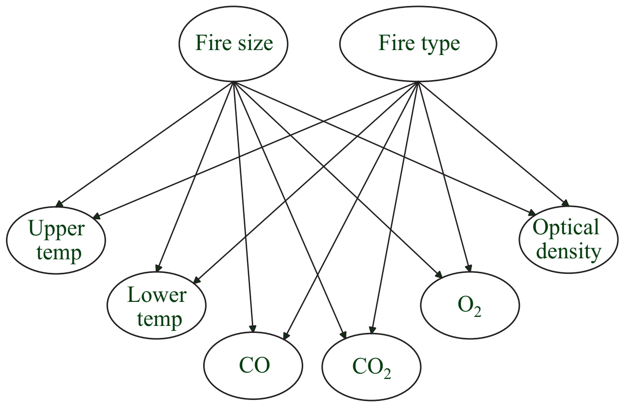


Fig. 3. Topological structure of identification model.

where $T_U, T_L, C_{CO}, C_{CO_2}, C_{O_2}, D_0$ represent upper temperature, low temperature, CO concentration, CO_2 concentration, O_2 concentration and optical density respectively. S_F, C_F denote fire size and type, respectively.

Directed lines set are expressed as

$$L = \{T_U S_F, T_L S_F, C_{CO} S_F, C_{CO_2} S_F, C_{O_2} S_F, D_0 S_F, \\ T_U C_F, T_L C_F, C_{CO} C_F, C_{CO_2} C_F, C_{O_2} C_F, D_0 C_F\} \tag{4}$$

If the input variables set are supposed as X_0, the conditional probability is obtained as

$$p([T_U, T_L, C_{CO}, C_{CO_2}, C_{O_2}, D_O] = X_0) = 1 \tag{5}$$

If the output variables set are supposed as Y_0, the conditional probability is given by

$$p(S_F, C_F) = 1 \tag{6}$$

Then, the probability distribution function of the output variables is expressed as:

$$p([S_F, C_F] = Y_0 \mid [T_U, T_L, C_{CO}, C_{CO_2}, C_{O_2}, D_O] = X_0) \\ = \frac{p([T_U, T_L, C_{CO}, C_{CO_2}, C_{O_2}, D_O] = X_0, [S_F, C_F] = Y_0)}{p([T_U, T_L, C_{CO}, C_{CO_2}, C_{O_2}, D_O] = X_0)} \tag{7}$$

where $p([T_U, T_L, C_{CO}, C_{CO_2}, C_{O_2}, D_O] = X_0, [S_F, C_F] = Y_0)$ is obtained by training sample data.

Thus, the maximum probability of fire size and type can be calculated using Eqs. (3)-(7).

3. Parameters Training

The training process of input and output parameters are realized using the Matlab toolbox FULLBNT. When the topological structure of the recognition network and continuous input and discrete output nodes are determined, the parameters of the network can be learned from sample data and the six input and two output parameters will be assigned with reasonable conditional probability value.

Table 1. Comparison of fire source parameters.

Parameters	Cable	Mattress	Pool fire	Spill fire
Fire category	Solid	Solid	Fuel oil	Fuel oil
Spread speed	Slow	Medium	Very fast	Very fast
Built-up time (s)	300	240	5~10	< 5

4. Model Evaluation

The objective of model evaluation is to demonstrate the validity of the trained model above by simulated sample data.

5. Model Validation

The objective of model validation is to validate the BN identification model by Full-scale experimental data.

V. VERIFICATION

To evaluate the validity of the trained model, 2880 groups of sample data are used to simulate integrated fire sensors. To validate the effectiveness of the BN identification model, 200 groups of experimental data are used to demonstrate integrated fire sensors.

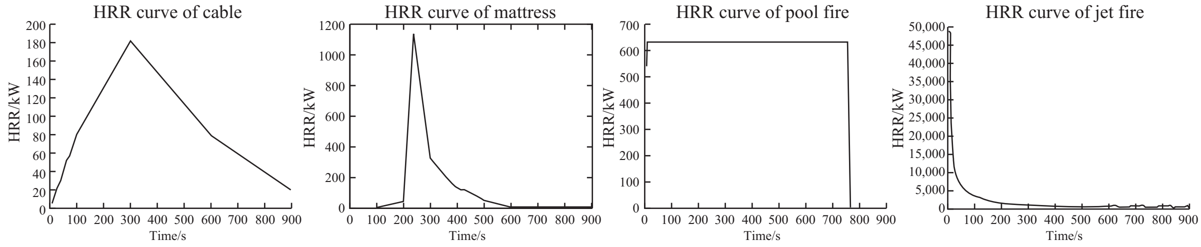
1. Simulation Evaluation

1) Simulated Sample Data

The simulated sample data used to train the parameters of the model are generated by CFAST. To maintain consistency in the simulation and validation environment, the experimental conditions, such as the fire source, ventilation status and compartment size, are identical. The engine room, hangar, combat command center and accommodation quarters are chosen as typical ship compartments. The cable fire, mattress fire, pool fire and spill fire are chosen as the fire sources, which represent typical flame spread speeds of slow, medium, fast and very fast (Williams and Scheffey, 1999; Williams and Tatem, 2000).

The heat release rate (HRR) curves of four types of typical fire sources are shown in Fig. 4. The fire development stages of ignition, development, maximum and recession are simulated on four types of compartments. Furthermore, five types of fire sensors that involve temperature, CO, CO_2, O_2 and optical density are simulated on each specific compartment.

Table 1 indicates that the parameters of built-up time and maximum HRR are different from the fire sources. The sampling interval of the simulated data is 5 s. Jet fires develop so rapidly that the time to reach the maximum HRR is less than 5 s and the temperature is higher than 500°C Therefore, the maximum stage is deemed as a large fire. The follow-up deve-



(a) Cable (b) Mattress (c) Pool fire (d) Jet fire

Fig. 4. HRR of different fire source.

Table 2. The parameters of compartment conditions.

Parameters	Accom-modation	Combat center	Engine room	Hangar
Compartment size (m)	4.5 × 5.5 × 2.5	5.5 × 11.4 × 2.5	13.0 × 9.0 × 5.7	15.5 × 5.5 × 6.5
Venting size (m)	0.65 × 1.65	0.65 × 1.65	0.65 × 1.65	4.50 × 4.50
Ventilation condition	Open	Open	Open	Open

Table 3. Serial number of sample data.

Fire source	Accom-modation	Combat center	Engine room	Hangar
Mattress	1~180	721~900	1441~1620	2161~2340
Cable	181~360	901~1080	1621~1800	2341~2520
Pool	361~540	1081~1260	1801~1980	2521~2700
Spill	541~720	1261~1440	1981~2160	2701~2880

lopment of a jet fire depends on the fuel oil quantity. If the supply is sufficient, the stage will remain as a large fire. Otherwise, the development stage will be turned into a medium fire or even a small fire. Table 2 shows the geometry and ventilation conditions of typical compartments. 2880 groups of sample data were obtained by CFAST, as shown in Table 3.

2) Fire Size

The total of 2880 groups of simulated sample data are manually classified into 1775 groups of small fires, 729 groups of medium fires and 376 groups of large fires.

The recognition results of fire size are presented in the form of probability, as illustrated in Figs. 5-7. To make data presentation more clearly, the horizontal axis uses logarithmic scale. The points on the longitude ordinate indicate that the total number of recognition results is 1 under the current probability. Setting the probability greater than 0.9 as the limited condition, 1683 groups of sample data are regarded as small fires, 667 groups are medium fires and 374 groups are large fires.

3) Fire Type

The simulated sample data consist of 1440 groups of solid

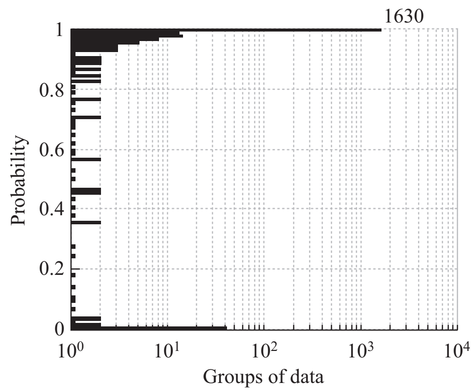


Fig. 5. Evaluation of small fire.

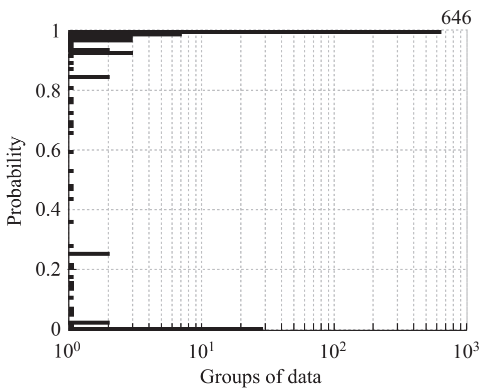


Fig. 6. Evaluation of medium fire.

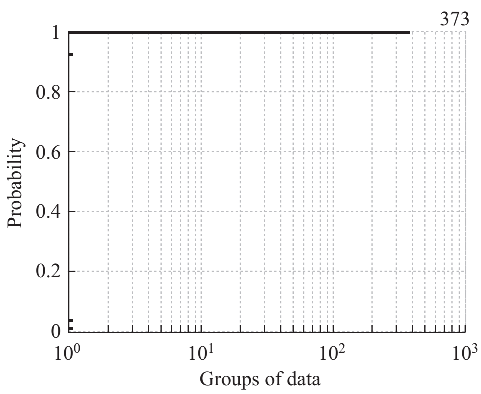


Fig. 7. Evaluation of large fire.

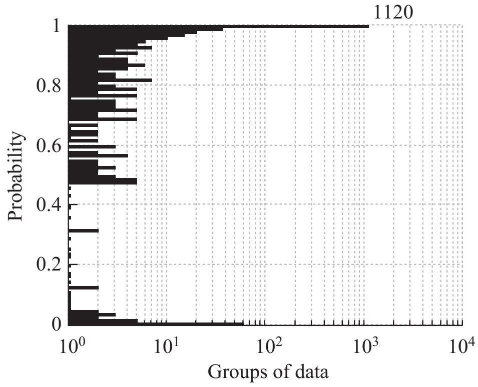


Fig. 8. Evaluation results of identifying solid fire.

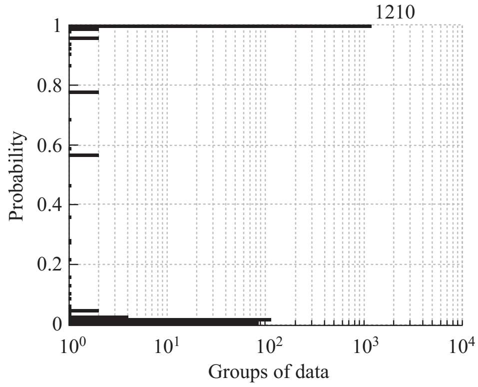


Fig. 9. Evaluation results of identifying fuel oil fire.

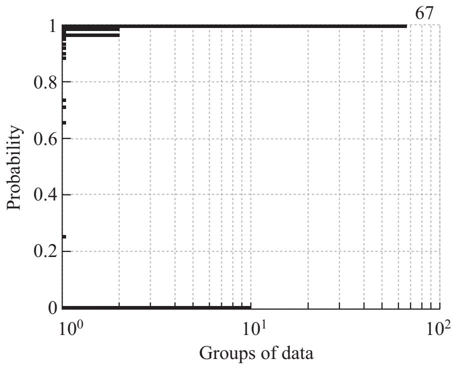


Fig. 10. Validation of small fire.

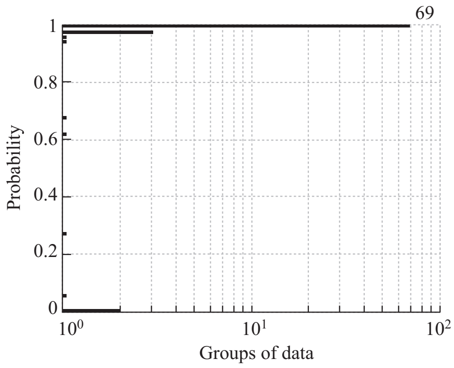


Fig. 11. Validation of medium fire.

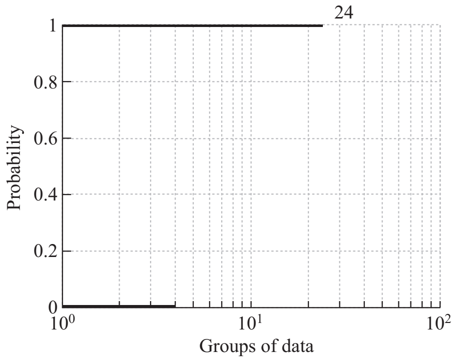


Fig. 12. Validation of large fire.

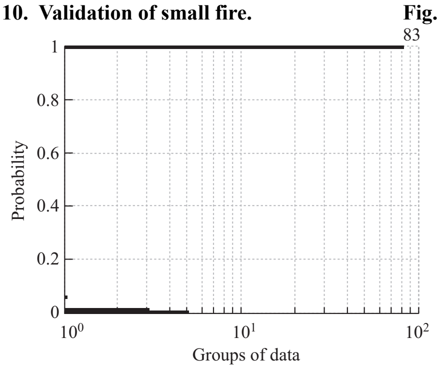


Fig. 13. Validation results of identifying solid fire.

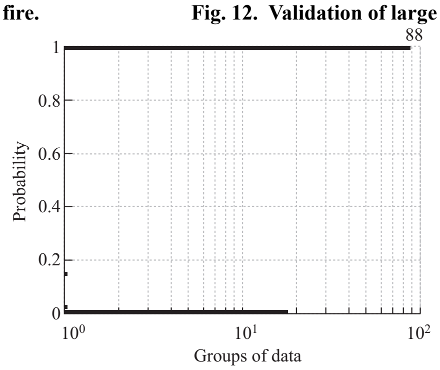


Fig. 14 Validation results of identifying fuel oil fire.

fires and 1440 groups of fuel oil fires. As shown in Figs. 8 and 9, 1228 groups and 1217 groups of simulated sample data are identified as solid fires and fuel oil fires, respectively, and reach a confidence level higher than 0.9.

2. Experimental Validation

200 groups of full-scale experimental data of were extracted from the reports from NRL (Wong and Gottuk, 2000; Hoover and Bailey, 2005; Hoover and Whitehurst, 2006) to validate the identification model.

1) Fire Size

Among the 200 groups of experimental data, there are 92 groups of small fire, 80 groups of medium fire and 28 groups of large fire. The experimental validation results of fire size are presented in Figs. 10-12. Setting the probability greater than 0.9 as the limited condition, Fig. 10 shows that 75 groups of experimental data are identified as small fire. Fig. 11 indicates that 74 groups are identified as medium fire, and 24 groups are identified as large fire in Fig. 12.

2) Fire Type

Among the 200 groups of experimental data, 92 groups are solid fire and 108 groups are fuel oil fire. As shown in Fig. 13 and 14, 83 groups and 88 groups of experimental data are identified as solid and fuel oil fires, respectively, reaching a confidence level higher than 0.9.

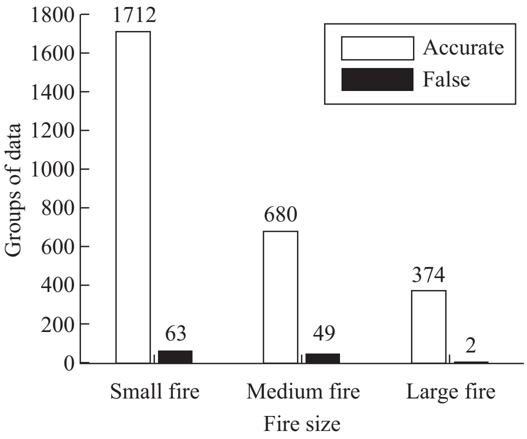


Fig. 15. Recognition rate of fire size with sample data.

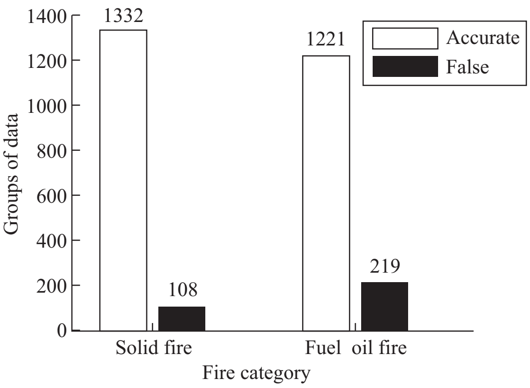


Fig. 16. Recognition rate of fire type with sample data.

VI. ANALYSIS AND DISCUSSION

Integrated and disintegrated sensor data are compared to evaluate the trained model and validate the BN identification model.

1. Comparison of Integrated and Disintegrated Simulation Data

Accurate and false recognition results of fire size are illustrated in Fig. 15. 63 groups of small fires accounting for 3.5% of the total are mistaken for medium fires. 49 groups of medium fires accounting for 6.7% of the total are mistaken for small or large fires. 2 groups of large fire accounting for 0.5% of the total are mistaken for medium fires. The average recognition rate of the sample data for fire size was 96.0%.

Accurate and false recognition results of fire type are illustrated in Fig. 16. 108 groups of solid fires accounting for 7.5% of the total are mistaken for fuel oil fires, and 219 groups of fuel oils fire accounting for 15.2% of the total are mistaken for solid fires. The average recognition rate of the sample data for fire type was 88.6%.

Because of serious fire accident or weapon discharge, fire sensors could not obtain valid data. As shown in Table 4, with the sample data failure of one sensor, average recognition rate with integrated simulation data. Average recognition rate of fire type is 86.3%, only 2.3% less than the recognition rate with integrated simulation data.

Table 4. Recognition rate with experimental data failure of one sensor.

Type of sensor failure	Fire size	Fire type
Upper temp (T_U)	91.4%	86.9%
Lower temp (T_L)	95.1%	84.8%
CO	93.1%	87.2%
CO_2	94.1%	88.2%
O_2	95.2%	85.2%
Optical density (OD)	92.3%	85.5%

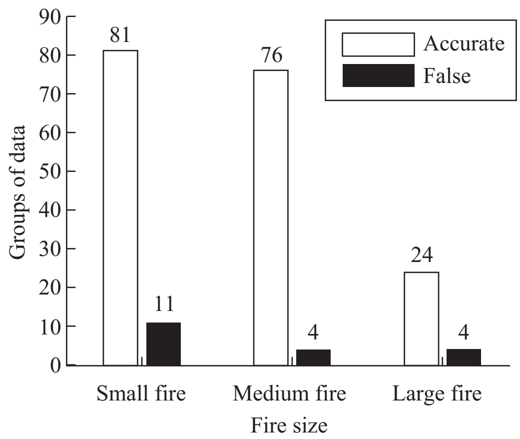


Fig. 17. Recognition rate of fire size with experimental data.

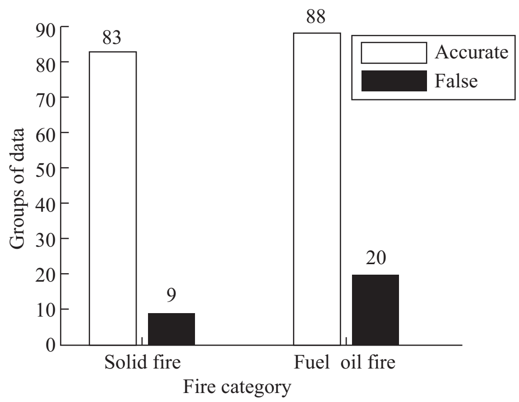


Fig. 18. Recognition rate of fire type with experimental data.

2. Comparison of Integrated and Disintegrated Experimental Data

Fig. 17 illustrates the accurate and false recognition rate of fire size. 11 groups of small fires accounting for 12% of the total are mistaken for medium fires. 4 groups of medium fires accounting for 5% of the total are mistaken for small or large fires. 4 groups of large fires accounting for 14.3% are mistaken for medium fires. The average recognition rate of fire size was 90.5%.

Accurate and false recognition results of fire type are illustrated in Fig. 18. 9 groups of solid fires accounting for 9.8% of

Table 5. Recognition rate with experimental data failure of one sensor.

Type of sensor failure	Fire size	Fire type
T_U	85.5%	82.5%
T_L	88.5%	84.0%
CO	82.5%	80.5%
CO_2	77.0%	85.0%
O_2	72.5%	83.0%
OD	88.5%	81.0%
Average	82.4%	82.7%

the total are mistaken for fuel oil fires, and 20 groups of fuel oil fires accounting for 18.5% of the total are mistaken for solid fires. The average recognition rate of fire type was 85.5%.

As shown in Table 5, given the data failure of one sensor, average recognition rate of fire size is 82.4%, only 8.1% less than the recognition rate with integrated experimental data. Average recognition rate of fire type is 82.7%, only 2.8% less than the recognition rate with integrated experimental data.

VII. CONCLUSIONS

The identification and management of fires that may lead to shipboard damage and crew danger are interesting areas of application for expert and decision support methods. Globally, large ships are enhancing the automation and intelligence of DCSS to achieve higher levels of security and operational efficiency through information fusion and visualization, damage identification, casual response and action planning.

In this paper, an intelligent sensor-based SFIS is presented that is capable of automatically identifying the size and type of fire to make timely and informed decision making. The system reduces damage recognition time, tactics planning time and action response time. Based on BN theory and fire development mechanisms, a novel fire identification model is proposed, which has outstanding advantage of dealing with accident uncertainty and data dis-integrity. The effectiveness of the proposed model is evaluated by simulated sample data and validated by full-scale experimental data.

The model developed for this research can be integrated into DCSS to further enhance the situational awareness of potential damage caused by shipboard fires. The application of SFIS will assist commanders in making critical decisions by indicating the most suitable suppression methods and tactics and by allocating the most efficient firefighting equipment and crew.

However, multiple sensor data failure is not studied in this paper. Future research will promote the recognition accuracy rate of shipboard fires under more complicated circumstances with incomplete and uncertain sensor data. A second area of development will expand the scope of combustion material recognition to metal fire and electrical fire within the ship context.

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