A Runway Incursion Situation Assessment Method Integrating Ontology and Bayesian Networks: Postprint

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Abstract

To predict the safety situation of airport surface operations, an integrated modeling approach combining ontology and Bayesian network (BN) is proposed to evaluate runway incursion severity values and facilitate optimal risk control measure decision-making. First, a domain ontology for runway incursion situation assessment is constructed based on the Threat and Error Management (TEM) model and subsequently transformed into a BN structure. Then, the BN model incorporating ontology semantic information is employed to learn from historical data, and evaluation metrics for runway incursion incident severity values are established. Finally, actual cases are analyzed to conduct optimal risk control decision-making. The results demonstrate that the runway incursion situation assessment system can effectively characterize the dynamic process of incident formation and evolution into runway incursion accidents, thereby providing an objective basis for optimal risk control decisions.

Full Text

Preamble

A Runway Incursion Situation Assessment Method Integrating Ontology and Bayesian Networks

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Abstract: To predict the operational safety situation of airport surfaces, this paper proposes an integrated modeling approach combining ontology and Bayesian networks (BN) to assess runway incursion severity values and support optimal risk control decision-making. First, a domain ontology for runway incursion situation assessment is constructed based on the Threat and Error Management (TEM) model and subsequently transformed into a BN. Next, the BN model, which incorporates semantic information from the ontology, learns from historical data to establish evaluation metrics for runway incursion accident severity values. Finally, a practical case is analyzed to determine optimal risk control decisions. The results demonstrate that the runway incursion situation assessment system can effectively describe the dynamic process of incident formation and evolution into runway incursion accidents, providing an objective basis for optimal risk control decisions.

Keywords: runway incursion; domain ontology; model transformation; threat and error management; Bayesian network

0 Introduction

Statistics from China' s civil aviation industry indicate that various types of runway incursion incidents at transport airports in recent years have seriously impacted surface operational safety. Runway incursion situation awareness constitutes a critical component of airport surface safety management, enabling the dynamic control of current safety levels and prediction of risk development trends from a systemic perspective. Surface operation safety departments can implement countermeasures based on risk situation assessment results to achieve runway incursion risk control.

The application of BN to study runway incursion problems has become a mature paradigm. Luo et al. [5] constructed a runway incursion causal diagram based on Gaussian BN to mine potential causes hidden beneath accident surface phenomena. Goodheart et al. [6] leveraged BN' s probabilistic inference mechanism to systematically study runway incursion by incorporating human, technical, and organizational factors. However, BN without semantic associations cannot adequately quantify uncertain semantic relationships, making it difficult to deeply mine risk assessment knowledge. Intelligent diagnosis technology based on ontology has been preliminarily studied for surface safety risk assessment [7,8]. Building upon this foundation, integrating ontology semantics with BN probabilistic inference—using ontology as a BN model structure database—can deduce the evolution mechanism of runway incursion threats and errors, providing a scientific basis for runway incursion prevention.

Ontology and BN integrated modeling technology has demonstrated successful applications in complex system risk assessment, prediction, and information mining, meeting the needs of intelligent information development for airport surface operational safety. Internationally, this integrated technology has enhanced automated decision-making capabilities in communication systems [1] and improved fault diagnosis efficiency in multimedia resource management systems [2]. Domestically, scholars have combined ontology and BN for uncertain information processing [3] and Web service reliability evaluation [4]. In this context, this paper proposes an ontology and BN integrated modeling approach. By analyzing the TEM model [9], the inherent logical relationships among runway incursion accident severity, dynamic performance of human work behavior, and changes in the surface operational environment are clarified. A domain ontology model is constructed and transformed into a BN, which learns from domestic runway incursion case data to obtain runway incursion situation assessment information.

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1 System Architecture

During airport surface operations, runway incursion occurrences relate to uncertain characteristic information regarding the work performance of controllers, pilots, and ground vehicle drivers, as well as changes in the surface operational environment. This paper proposes constructing a runway incursion situation assessment system whose architecture is shown in [Figure 1: see original paper]. The system is primarily divided into a knowledge application layer and a semantic description logic control layer, corresponding to the probabilistic information processing stages from domain ontology creation to BN inference. These layers encompass processes such as knowledge integration, model transformation, and model parameter adjustment. Domain knowledge is formally defined, with ontology concepts and relationships extracted and converted into a BN. The BN learns from actual runway incursion case data to derive objective probabilities of runway incursion threats, errors, and severity, enabling risk situation assessment and optimal decision-making.

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2 Ontology Model

2.1 Ontology Construction

The Threat and Error Management (TEM) model facilitates understanding of safety situations and human performance in dynamically changing operational environments from an operational perspective. A domain ontology refers to a collection of concepts and their relationships and attributes within a specific field. This paper establishes a reference terminology set through the TEM model, combined with China's civil aviation air traffic control guidance materials for runway incursion prevention [10] and the current state of domestic surface operational safety. Using OWL 2 DL language and a top-down approach, the domain ontology is constructed on the ontology editing platform Protégé 4.2. The runway incursion threat and error domain ontology contains 38 classes, 51 relationships (42 object properties and 9 data properties), and 30 instances. The core concepts and relationships of the runway incursion threat and error ontology model are illustrated in [Figure 2: see original paper].

The severity (RI_severity) class includes four instances, with instance LevelA representing the highest severity level, instance LevelB the second highest, and remaining instances representing sequentially decreasing severity levels. Severity is a crucial indicator for runway incursion situation assessment. China' s civil aviation classification of runway incursion accident severity aligns with the International Civil Aviation Organization (ICAO), using five levels A, B, C, D, and E, though Class E incidents are generally not considered due to insufficient information or contradictory evidence.

The error class causing runway incursion can be divided into error type class (ErrorType, ET) and error factor class (ErrorFactors, EF). The ET class includes primary human error class (PrimaryHumanError, PHE) and operational error class (OperationalError, OE). The PHE class contains ATC issues class (ATCIssues), flight crew issues class (FlightCrewIssues), and driver issues class (DriverIssues). The OE class comprises two-party communication issues class (TwoPartyCommIssues) and surface issues class (SurfaceIssues).

The collision scenarios class (CollisionScenarios) describes conflict scenarios between aircraft and between aircraft and ground vehicles during runway incursion. The attribute class is used to set data properties for subclasses of RI_severity and error classes.

2.2 Ontology-to-BN Conversion

Ontology can be structurally summarized as O: (C, R, A, T, I), representing domain concepts, concept relationship sets, class characteristics, class characteristic sets, and instances, respectively. A BN is a directed acyclic graph that can be represented as B=«V,E>,P>, where V={V1,V2,···,Vn} is the variable set; E is the directed edge set; and P represents the set of conditional probability tables for nodes. The conversion from ontology to BN primarily includes:

a) A class Ci in the ontology is converted to a node Vi in the BN.

b) If a relationship (object property) Rj exists between class Ci and class Ci+1 in the ontology, the directed edge Ej connecting nodes Vi and Vi+1 in the BN is the conversion of Rj.

c) The characteristics (data properties) ACi of class Ci in the ontology control the data type of BN node Vi, and the instances ICi contained in class Ci are converted into state variables of node Vi.

Weather, conflict location, and other factors in runway incursion scenarios are external force majeure factors; therefore, this paper does not consider the conversion of the collision scenarios class. The structured semantic elements of the above ontology are extracted, and the FaCT++ reasoner in the model transformation control unit is used to verify the semantic consistency of the extracted model. If the model meets semantic requirements, it is converted into a BN model using the BNTab 1.1.3 plugin and Netica_J 4.18; otherwise, the semantics must be refined before re-conversion. [Figure 3: see original paper] shows the working interface of the model conversion plugin.

The partial pre-compiled code for generating the runway incursion situation assessment BN is as follows:

```
RI_Severity;Type I Class;Single Class;SeverityAttriute;
hasSeverityAttribute;
OperationalError;Type I Class;Single Class;
ErrorAttributes;hasErrorAttribute;
hasOperationalError;Type I Property;false;false;
hasPrimaryHumanError;Type I Property;false;false.
```

The RI_Severity class is converted to a BN node, data properties hasSeverity-Attriute and the SeverityAttriute class are converted to BN node state spaces, and object properties hasOperationalError and hasPrimaryHumanError are converted to BN directed edges.

2.3 BN Model Improvement

2.3.1 BN Node Analysis The main node attributes in the BN include consequences, errors, and threats. presents the variable assignments and detailed classifications for each node. The child node RI_severity contains four state spaces (Levels A–D), while parent nodes PrimaryHumanError and OperationalError are Boolean nodes. The three exhibit causal mechanism independence and obvious multi-state system characteristics [11].

2.3.2 BN Model Enhancement The Noisy-Or model is a typical causal mechanism independence model, but its node types must be Boolean variables, limiting its applicability. The Noisy-MAX model extends the Noisy-Or model' s state space, providing a new solution for constructing BN models to handle complex multi-state system problems [12]. For the Noisy-MAX model, let Zi represent the i-th possible value of the child node set Y, and Pa(Y)={X1,⋯ ,Xn} represent the parent node (cause) set of child node Y. The probability that parent node Xi takes value x while child node Y=Zi is denoted as P(Y=Zi|Xi=x). The Noisy-MAX model probability distribution is:

$$P(Y \leq y|X_1 = x_1, \dots, X_n = x_n) = \prod_{i=1}^{n} P(Y \leq y|X_i = x_i)$$

The Noisy-MAX model variable probability calculation formula is:

$$P(Y = y|X_1 = x_1, \dots, X_n = x_n) = f_{MAX}(z_1, \dots, z_n)$$

where $f_{MAX}(z_1, \dots, z_n) = \max(z_1, \dots, z_n)$.

Knowledge modeling methods may be subject to interference from unknown causes, leading to confidence bias during probability assessment using the Noisy-MAX model [13]. By introducing a leak variable ZL, the Noisy-MAX model is improved to the Leaky Noisy-MAX model. With variable leak parameter c_L and cumulative vector parameter C_L, the formula can be improved as:

$$P(Y \leq y|X_1 = x_1, \dots, X_n = x_n) = \left(1 - \prod_{i=1}^{n}(1 - P(Y \leq y|X_i = x_i))\right) \cdot (1 - c_L) + c_L \cdot P(Y \leq y|Z_L)$$

3 Severity Assessment and Optimal Decision

3.1 BN Initialization

Netica 5.18 is used as the BN probability analysis tool to identify the model transformation file, learn case data, complete probability correction, assess runway incursion situations, and conduct optimal decision-making. Fifty-three runway incursion cases occurring domestically from 2015–2016 were collected as samples. Partial BN node variable states were ambiguous, leading to information loss. After sample data preprocessing, the Expectation Maximization (EM) algorithm [14] was employed for data learning to obtain initial prior probabilities. Based on this, the multi-state BN node RI_Severity was corrected according to the formula. The improved ICI node probability relationship is shown in .

Based on the improved initial prior BN, the Accident Severity Index (ASI) evaluation metric is proposed to assess runway incursion situations. The ASI is defined as:

$$ASI_j = \sum_{i=1}^{N} V_i \cdot P_i$$

where V_i represents the loss corresponding to severity characteristic level i, P_i is the probability of severity characteristic level i accident under a specific accident j, and N is the number of accident characteristics.

According to existing runway incursion severity level mathematical models [15], the four severity characteristics A, B, C, and D of runway incursion are quantified as $V_A = 4$, $V_B = 3$, $V_C = 2$, and $V_D = 1$. The ASI value range is defined as $[2.50, 4.0]$, representing a severe risk situation. The quantized intervals for severity characteristics C and D are $[1, 2.50)$, representing a general risk situation. The discrete classification standards for ASI indicators corresponding to each severity level are derived as shown in .

3.2 No-Strategy Situation Assessment

Taking the "Shanghai Hongqiao 10.11" runway incursion accident as an example: the tower controller forgot aircraft status (lost situational awareness), flight MU5106 crew turned off the transponder (communication equipment problem), violated ATC instructions to wait in position, and accelerated across runway 36L-18R occupied by flight MU5643. The MU5643 flight crew performed an emergency takeoff maneuver to avoid the accident. In this incident, ground vehicle drivers and airport surface conditions posed no threats.

Using the node information recorded in the accident report as evidence in the BN, the ASI for the "Shanghai Hongqiao 10.11" runway incursion accident is calculated as 2.571 ([Figure 4: see original paper]), indicating a severe runway incursion situation assessment result. The posterior probabilities of DriverNormal (driver performance normal) and SurfaceNormal (surface normal) are 99.9%, and the probabilistic inference results highly match the accident investigation conclusions. The case analysis demonstrates the feasibility of the integrated ontology and BN runway incursion situation assessment method.

3.3.1 Single Control Measures

To analyze the impact of specific threat causes on runway incursion situations, control measures are implemented and changes in the severity node risk situation are observed. The node output value ASI serves as the utility indicator for evaluating control schemes. According to runway incursion emergency response procedures, risk control schemes are proposed targeting errors affecting runway incursion from the perspectives of management and emergency command of ATC operation units, resident operation units (military, airlines), and airport operation departments. Detailed measures are presented in .

Based on these control schemes, changes in the overall ASI value are observed after adding individual control measures to the runway incursion situation assessment BN. For the "Shanghai Hongqiao 10.11" runway incursion accident, the original output value ASI is 2.571. If control measure #1 is implemented —avoiding controller situational awareness loss—the state space of the "ATCIssues" node in the runway incursion situation assessment BN model is adjusted from P(ATCCommFail)=0, P(ATCLostSA)=100, P(ATCNormal)=0 to P(ATCCommFail)=0, P(ATCLostSA)=0, P(ATCNormal)=100. The adjusted runway incursion risk situation is shown in [Figure 5: see original paper], yielding an adjusted output value ASI of 2.482, representing 96.53% of the original output value. The evaluation formula is:

$$\frac{ASI_1}{ASI_0} \times 100\% = 96.53\%$$

Utility ranking results show that implementing single risk control measures yields insufficient improvement in runway incursion situations, failing to meet practical needs for reducing surface operational safety risks. Therefore, combined risk control schemes are developed based on individual measures: Scheme 1 simultaneously adopts control measures 1 and 5; Scheme 2 simultaneously adopts control measures 3 and 5; Scheme 3 simultaneously adopts control measures 3 and 4.

The ASI changes under these combined risk control schemes are calculated, with results shown in .

3.4 Example Analysis

From , combined scheme 2 (improving crew emergency handling capabilities, enhancing crew awareness of strictly following ATC instructions, and standardizing communication phraseology while improving coordination mechanisms between ATC units and crews) emerges as the optimal control strategy. Combined scheme 3 (enhancing crew compliance with ATC instructions and intensifying surface movement area safety hazard investigation to improve surface safety management capabilities) ranks second in utility, followed by combined scheme 1 (strengthening controller business skills training, improving controller safety awareness, and standardizing communication phraseology while improving coordination mechanisms among all units). The three combined control schemes can reduce ASI values to 72.22%, 76.55%, and 79.15% of the original runway incursion ASI value, respectively—demonstrating more significant runway incursion risk situation reduction compared to individual risk control measures.

By analyzing correlations between flight crew and ATC errors and operational environmental threats: flight crews are more susceptible to surface operational environment changes than controllers; communication threats between crews and controllers constitute the primary cause of flight crew errors, with threat levels exceeding those posed by airport lighting and ground markings.

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4 Conclusion

a) The runway incursion situation assessment system integrating ontology and BN leverages the semantic description advantages of ontology to resolve heterogeneous information issues in surface operational safety assurance, while utilizing BN' s probabilistic inference mechanism to enhance surface operational risk management capabilities.

b) Based on learning results from multiple domestic runway incursion accident reports, case analysis demonstrates that the constructed system can provide reasonable runway incursion situation assessment services for surface operational safety assurance units, validating the feasibility of the proposed method.

c) Targeting threats and errors involved in current runway incursion accident evolution processes, five risk control measures and three risk control schemes are proposed, providing quantitative reference bases for accident loss reduction decisions by surface operational safety assurance units.

d) The proposed assessment method primarily focuses on human factors and management aspects; subsequent research will incorporate weather, conflict scenarios, and other factors for comprehensive analysis to broaden the application scope of runway incursion risk assessment.

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Note: Figure translations are in progress. See original paper for figures.