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A Review on Risk Assessment Methodologies of Decision-making for Virtually Coupled Trains

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When virtually coupled trains are applied in the real world, there is a need to consider the associated risks stemming from unknown and unforeseen situations. This then requires decision-making systems of virtual coupling to be able to make appropriate decisions autonomously in the face of environmental and behavioral uncertainties and, more importantly, be able to perform appropriate risk assessments prior to decision-making. We provide an overview of risk assessment methodologies for virtually coupled trains decision-making in terms of both quantitative and qualitative analysis, respectively. Among them, the quantitative analysis methods can be further divided into three parts: risk identification, risk measurement and risk reasoning. By comparing the differences of each method, we find that the probabilistic approach can better handle the uncertainty of the input information of the decision-making system. Finally, we propose future research directions.

Keywords: Risk assessment, Virtually coupled trains, Uncertainty, Quantitative method, Qualitative method.

1. Introduction

Railway transportation, as a safety-critical system, requires that trains are safe in their own right in the environment in which the trains operate, so the trains must be able to reliably predict and assess collision probability in any given situation. To achieve this, trains must have a reliable, robust and comprehensive risk assessment (RA) methodology.

Traditional fixed group trains face the problem of non-synergy between passenger demand and capacity. In order to overcome the problems faced by traditional fixed grouping methods, flexible grouping is developed to achieve the best synergy between passenger demand and capacity. Train formation operation is also known as Virtual Coupling, and the trains are connected to each other by train-to-train communication instead of actual hooks, which enables them to combine and operate together freely (Stickel et al., 2022).

According to the existing train operation control mode, the ground zone controller (ZC) generates movement authorization (MA) based on the position information of the preceding train, and the train develops its own speed control strategy based on the MA. Unlike fixed blocking, absolute braking distance mode (ADBM) and relative braking distance mode (RDBM), virtual Coupling requires much lower spacing between trains, and traditional safety protection methods cannot be applied to virtual Coupling. Virtually coupled trains should be autonomous and on-demand, rather than just running on a fixed schedule (Henke et al., 2008).

Unlike decision-making under determinism, decision-making under uncertainty is probabilistically unknown and risky. A fundamental characteristic of an agent is its ability to autonomously perceive, act and learn in a dynamic uncertain environment and to make decisions under uncertainty. Therefore, in order to achieve autonomous decision-making in for virtually coupled trains, RA is necessary.

There is no uniform solution for RA and many methods exist. Since the model of car-following in a single lane is similar to the model of virtually coupled trains, this paper also investigates the RA method for car-following decision-making.

This paper is organized as follows: first, the risks faced by virtually coupled trains of decision-making are analyzed in section 2, and the methodologies of RA from quantitative and qualitative perspectives are described in sections 3 and 4, respectively. In section 5, we summarize and propose some possible research directions about these RA methodologies.

2. Risks to Decision-making for Virtually Coupled Trains

The virtually coupled trains must ensure a certain level of safety in order to be accepted by society and regulatory agencies. At the same time, train operations must not be too conservative or the requirements of short interval tracking cannot be met. IRSE news [a] questions the safety of virtually coupled trains, arguing that safety depends on a variety of factors and requires more difficult safety arguments considering aspects such as the designed operating mode, the possibility of control or mitigation measures, and that it cannot simply be assumed that virtually coupled trains are less safe than single trains. However, safety does not mean risk-free. Möller (2012) proposed a theoretical definition of safety decision-making applicable to a wide range of domains and systems, defining safety as the reduction or minimization of risk and cognitive uncertainty.

The input and output signals of virtually coupled trains decision-making system are shown in Figure 1. From the figure, it can be seen that the key situational information includes:

- External environment information: obstacle, weather, equipment status and status of the preceding train.
- Ego-train information: self status, number of passengers and energy consumption.
- Human-prescribed information: pre-planned operating diagrams.

During the train operation, there is uncertainty in other information except for the human-prescribed operation diagrams. High-speed trains and heavy haul trains are located outdoors and are more susceptible to weather. Obstacles refer to objects on or near the tracks that are not part of the railroad infrastructure, such as construction workers, leftover tools and foreign objects that encroach on the limits. Due to the limitations of sensors, trains do not have a clear understanding of their surroundings.

In short, there are random disturbances in the external environment and uncertainties in the parameters of its own dynamic characteristics, thus posing risks to the train. Decision-making for virtually coupled trains needs to consider how to deal with the risks caused by uncertainties and output the correct decision-making information.

Several methods have been used for virtually

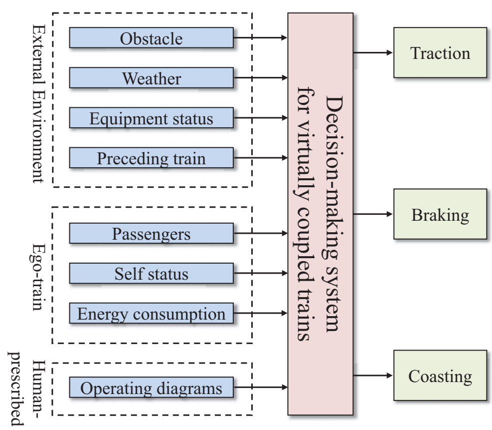

Fig. 1. The input and output signals of virtually coupled trains decision-making system

[a] https://webinfo.uk/webdocssl/irse-kbase/ref-viewer.aspx?refno=1882928268&document=itc%20report%2039%20train%20convoys%20and%20virtual%20coupling.pdf

coupled trains decision-making, such as model predictive control (Vaquero-Serrano and Felez, 2023) and reinforcement learning (Wang et al., 2021). However, many decision-making methods do not adequately consider driving risks, and risk-insensitive decision-making methods may lead to unsafe train operations. Therefore, it is essential to perform RA before decision-making.

After RA, general determinations can be made and the decision-making module can be alerted to future risks. However, these methods cannot be used directly for autonomous decision-making, so specialized decision-making modules are also needed to determine the appropriate behavior (Xu et al., 2020). Both RA and collision avoidance decisions are essential modules in virtually coupled trains.

In addition, there may be uncertainties in the methods used for decision-making. In recent years, with the development of artificial intelligence (AI), intelligent perception technology and intelligent control technology have been introduced into the field of train operation control, and a class of Intelligent Awareness-based Train Driving Assistance System (IATDAS) has started to emerge. This type of system makes the train have the function of detecting the train, people or other obstacles in front of them autonomously. At the same time, however, should there be a safety issue with the IATDAS system, it would potentially cause a train operation accident. Therefore, the model itself for decision-making using AI may also be risky (Chia et al., 2022). However, the risks present in the decision module itself are not the subject of this paper, which focuses on the risks of the input information.

3. Quantitative Methods

For quantitative RA, research tends to focus on the following three areas: risk identification, risk measurement, and risk reasoning.

3.1. *Risk Identification*

Risk identification refers to the prediction of other traffic participants based on their trajectories to determine whether they will have a collision risk to ego-train. The ego-train can only detect information such as the spatial state of the train and obstacles around itself, and cannot detect their future motion, making risk identification difficult. The methods related to risk identification can be divided into three categories: physics-based methods, maneuver-based methods, and interaction-based methods (Lefèvre et al., 2014).

The physics-based approach derives the future motion of the target train based on a dynamics model or a kinematic model, and the identification of potential risks is based on a motion model. However, this approach is limited to short-term motion prediction, since it considers only low-level motion characteristics and does not consider the execution of actions such as sudden acceleration or deceleration.

For this reason, some scholars have introduced a maneuver-based risk identification approach (Lefèvre et al., 2014). This approach estimates the most likely driving behavior to be performed next based on the behavior that the target train intends to perform, which in turn predicts the future motion of the target train, and identifies potential risks through the long-term motion predictions derived from the behavior. Thus, this approach provides a more reliable risk identification. The interaction-based approach considers not only the kinematic state of the target train, but also the interaction between multiple trains, and analyzes the game driving process between several trains based on the driving behavior characteristics. These two methods are more researched in road vehicles. These two methods are less used in the rail transportation field due to the need to develop operation diagram in advance to specify the trajectory of trains.

3.2. *Risk Measurement*

Studies related to risk measurement often focus on the selection of appropriate risk metrics to assess potential risks in the operational environment, such as time to collision (TTC), headway time distance (THW), time to braking (TTS), and time to reaction (TTR) (Dahl et al., 2019).

TTC is usually used in the longitudinal direction because it is time-based and combines speed difference and spatial proximity. In general, the

TTC is calculated as:

$$\mathrm{TTC} = \frac{D_r}{v_r} \tag{1}$$

where D_r is the relative distance between the two trains and v_r is the relative speed between the two trains and the speed of the preceding train is smaller than that of the following train.

The calculation of TTC in the case of virtual coupling is shown in Figure 2 and Figure 3, the dashed line is the speed distance curve of train braking. TTC does not consider the potential conflict area, i.e. the area where the future motion of two trains will intersect, so it can only be used in the case of section operation on the same track. When running in the section, due to the special nature of the tracks, only backward and forward tracking of trains on the line exists, and no crossing or yielding occurs, so the calculation of TTC is relatively simple. However, when the train is close to the station, the calculation of TTC will be more complicated due to the possible intersection of tracks and the existence of intersection of the running lines of two trains, which can form a Y-shaped virtual coupling, and the calculation of TTC needs to consider the conflict area, i.e. turnout.

In the field of road traffic, a new concept of responsibility-sensitive safety (RSS) (Shalev-Shwartz et al., 2018) was proposed to derive the collision avoidance condition for AV (Autonomous Vehicle) using a reasonable estimation of the worst-case scenario, where the minimum longitudinal safety distance in the car-following mode is the difference between the driving distance of the following vehicle and the braking distance of the preceding vehicle. And it was demonstrated that safety is ensured as long as the distance between two vehicles is satisfied to be greater than the formal safety distance. However, some scholars believe that this condition is too conservative and deterministic and has limitations.

In conclusion, these risk metrics are unable to model the uncertainty of situational information for display, and some scholars use probabilistic risk metrics. Probabilistic risk metrics use probabilities to describe spatio-temporal relationships and risk levels.

Due to factors such as sensor errors, there is uncertainty in the state perception of the train, and the trajectory of the preceding train perceived by the following train is not necessarily the actual value. As shown in Figure 4, the shaded part indicates the possible trajectory envelope of the preceding train. Let O_k^i be an estimate of the current position state of train i at moment t_k, and S_k^i be the real position state of train i at moment t_k. If no data are available, then the probability density function $f(S_k^i)$ of all possible position state estimates of train i at moment t_k can be simply expressed by Gaussian distribution as

$$f\left(S_k^i; O_k^i, P_k^S\right) = \frac{1}{\sqrt{2\pi P_k^S}} \mathrm{e}^{-\frac{\left(S_k^i - O_k^i\right)^2}{2P_k^S}} \tag{2}$$

where P_k^S is the variance of the location state estimate. Instead of assuming that the uncertainty has a Gaussian distribution, if the data are available, a sampling-based approach is used, which is capable of handling more general uncertainty probability distributions (Cai et al., 2021).

Representing risk measures with probability distributions can deal with uncertainties caused by measurement noise or different behavioral possibilities of traffic participants. Some scholars have proposed probabilistic TTC (PTTC) based on TTC (Berthelot et al., 2012). When there is adverse weather such as rain or fog, trains located in outdoor track sections need to consider the effect of different weather on perceptual performance and braking performance when calculating PTTC. Shin et al. (2019) use the number of collision cases within the uncertainty boundary as a risk metric.

Besides PTTC, there are some other risk metrics. Majumdar and Pavone (2020) analyzed the commonly used risk metrics and their properties and concluded that the three risk metrics of conditional value-at-risk (CVaR), expected cost, and worst case satisfy six axioms of monotonicity, translation invariance, positive homogeneity, subadditivity, comonotone additivity, and law invariance, and are called coherent risk metrics. Figure 5 provides a graphical representation of the meaning of CVaR, expected cost and worst-case scenario.

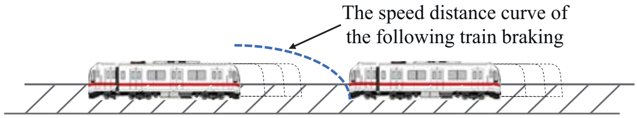

Fig. 2. TTC calculation for virtually coupled trains at the section

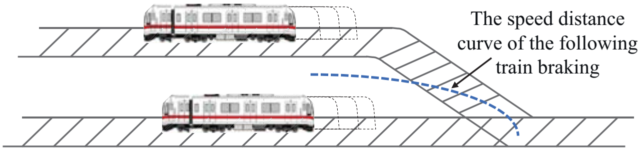

Fig. 3. TTC calculation for virtually coupled trains at the station

Among them, CVaR is a widely used coherent risk metric that has been used in various decision problems. The risk CVaR_α for a stochastic cost Z with probability α is defined as

$$\mathrm{CVaR}_\alpha(Z) := \frac{1}{\alpha}\int_{1-\alpha}^{1} \mathrm{VaR}_{1-\tau}(Z)\mathrm{d}\tau \qquad (3)$$

where VaR_α refers to the value-at-risk with probability α. As shown in Figure 5, the shaded part represents the tail part of the probability α and CVaR is the expected value of the shaded part. The use of CVaR to assess risk allows to dynamically adjust the behavior of the whole system from aggressive to highly conservative by changing a single value, i.e., the level of risk probability (Fan et al., 2021).

Bernhard et al. (2019) achieved safer decision-making by designing corresponding risk quantification models for uncertain movements of traffic participants. CVaR is used to quantify uncertainty in the environment based on an easily interpretable risk metric. Chow et al. (2015) considered a risk-sensitive MDP (Markov Decision Process) with a CVaR optimization objective. CVaR MDPs use a more general risk metric instead of the optimization objective of cumulative returns in traditional MDPs, allowing dynamic adjustment of the level of risk willing to be accepted and without ignoring tail events with low probability of occurrence but high consequences.

3.3. *Risk Reasoning*

Risk reasoning means analyzing the level of risk based on the results of risk measurement.

The methods associated with risk reasoning can be divided into two categories: deterministic methods and probabilistic methods. Under the deterministic methods, the likelihood of collision with a potential risk is calculated in the form of a binary prediction based on predetermined thresholds by means of a simplified motion prediction model and various risk metrics. The deterministic methods are binary predictions that estimate only whether a potential collision will occur.

In addition to the binary approach, it is possible to classify the level of risk into specific levels based on the value of the risk measurement, similar to Risk Matrix. Li et al. (2021) classifies the risk level into Dangerous, Attentive and Safe and calculates the risk level based on the results of TTC and TTS calculations. Li et al. (2018), however, classifies the risk level into four classes as red, orange, yellow and blue, and calculates the risk level of the train based on the time to avoid collision (TAC) and TTC.

In addition, the formal approach uses formal verification based on rigorous mathematical definitions to precisely solve the reachable range of unsafe states for trains in the current state at a predetermined time, and thus assesses the safety of various decision-making. Liu et al. (2022) proposed a safety protection method for virtually cou-

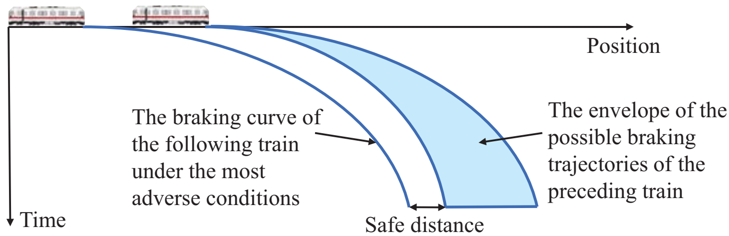

Fig. 4. Uncertainty in state perception

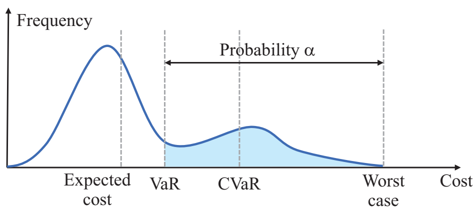

Fig. 5. Illustration of risk metrics

pled trains based on reachable sets.

Deterministic methods have been used for collision avoidance systems in a variety of fields because they are both simple and computationally efficient. However, it does not take into account the uncertainty of the input data. Therefore, some scholars use probabilistic methods for risk reasoning, such as fuzzy logic, Bayesian networks, and Dempster-Shafer (DS) theory.

So far, there are many methods to estimate unknown parameters from data, and Bayesian inference is a very popular method among the many methods. One of the main advantages of Bayesian methods is their ability to quantify uncertainty while inferring (Gelman et al., 2013). Thus, dynamic Bayesian networks (DBNs) can easily adapt and modify the latest observations and new knowledge and are widely used in risk reasoning problems with dynamic uncertainty. Noh (2019) and Noh and An (2018) used Bayesian network models to combine conventional metrics (e.g., TTC) into risk probability assessments.

DS theory has the ability of evidence fusion and evidence inference to synthesize individual risk terms based on the information available from different sources, reducing the uncertainty in the overall system security risk assessment (Kang et al., 2020). Fuzzy logic is usually combined with other methods to achieve risk reasoning by combining the advantages of multiple methods (Claussmann et al., 2018).

4. Qualitative Methods

Qualitative RA uses other known process tools to identify root causes of potentially identified failures, including hazard and operability studies (HAZOP), failure mode effects and hazard analysis (FMECA), fault tree analysis (FTA), and failure mode and effects analysis (FMEA).

In addition to the traditional approaches, there are several systems models and methods that can explain the effects of interactions in systems, such as the Functional Resonance Accident Model (FRAM) (Tian and Caponecchia, 2020) and System Theoretical Process Analysis (STPA) (Leveson, 2012). In the systems approach, safety is considered as an urgent issue that should be analyzed in the context of complex interactions of socio-technical systems. Within the railroad sector, attempts have been made to use the system's analysis approach for risk analysis. Zhang et al. (2021) used STPA for risk analysis of IRDAS to identify risk factors.

Hao et al. (2020) used STPA for risk analysis of virtually coupled trains to identify some potential hazards that are difficult to detect by traditional safety analysis methods, which helps to assist in system safety decision-making.

With the rapid development of AI (especially deep learning) in recent years, some scholars have used AI methods for RA in addition to the quantitative and qualitative methods mentioned above. However, AI may learn unsafe behaviors that were not intentional to begin with. AI methods, if used alone, may instead increase risk, especially if developers lack an inherent understanding of their use for risk analysis requirements. Therefore, AI methods may require more real-time testing and verification than classical methods such as process-based, probability-based, and model-based approaches (Chia et al., 2022).

5. Discussion and Conclusion

When deploying virtually coupled trains, an autonomous system, in the real world, the associated risks stemming from unknown and unforeseen situations need to be considered. This requires that the autonomous system be able to make appropriate decisions in the face of environmental and behavioral uncertainties and, more importantly, to perform appropriate RA prior to the decision-making.

RA can be broadly divided into quantitative and qualitative analysis methods. Among them, quantitative analysis includes risk identification, risk measurement and risk reasoning. In addition, RA can be classified as deterministic and probabilistic. It is worth noting that sometimes the boundaries between the different categories are subtle, so overlap between the selected categories is inevitable.

Using deterministic risk metrics can only assess the threat risk of the current state, whose performance will deteriorate if the driving behavior of surrounding trains changes, and does not take into account the uncertainty of the input information. The use of probabilistic methods for display modeling of uncertainty in situational information can reduce potentially unknown and unsafe situations and is the future direction of RA.

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