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A Statistical Model Checking Approach to Reliability Assessment of Railway Marshalling-Yard Operation Plans

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SUMMARY: *Railway marshalling yard operation is developing towards high density, fast turnover and fine scheduling, which puts forward higher requirements for reliability verification of hump disassembly plan. The operation plan of a railyard involves discrete events such as train arrival, locomotive occupancy, hump authorization, carriage roll-off and fault recovery. Traditional empirical verification is difficult to accurately describe the completion probability under random disturbances. In this paper, statistical model checking method is used to analyze the reliability of railway marshalling yard operation plan. In this paper, the main controller, train, shunting locomotive and hump signal system are abstract as timed automata with stochastic time semantics. The synchronization channel is used to describe the events of unwinding start, roll-off success, roll-off failure and recovery confirmation. The results show that the number of cars in track 1 converges from 5 to 7, the unrecoverable failure probability is 0.48%±0.01%, and the completion probability of Train(2) reaches 0.9558 at 330min. Disturbance experiments show that the arrival rate and recovery rate will change the controller state occupancy time and the tail train completion probability. The results show that statistical model checking can provide quantitative verification basis for reliability evaluation of railway marshalling yard operation plan.*

KEYWORDS: *Railway marshalling station; Statistical model checking; Sequential automata; Reliability evaluation*

1 Introduction

With the development of railway freight organization to high density, fast turnover and fine scheduling, the tasks of train disintegration, carriage classification and regrouping in the hump area of marshalling station are more concentrated. There are mutually exclusive relations among receiving field, shunting locomotive, hump signal system and classified track, and the waiting, roll-off deviation or recovery delay of any link will change the completion probability of the original plan. Traditional empirical verification relies on static schedules and manual reasoning, and it is difficult to describe random arrival, equipment occupancy, state synchronization and failure recovery in the same computational framework, which leads

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to the lack of quantitative evidence before the plan is implemented.

Formal methods provide a computable modeling basis for railway operation systems. Basile et al. studied the formal modeling experience of ERTMS/ETCS and showed that timing constraints and operating states could be transformed into verifiable models [1]. James et al. proposed a domain-oriented formal method framework for railway design, emphasizing that the model semantics should be close to the real operation object [2]. Ferrari et al. evaluated the usability of formal tools in the design of railway signaling systems and proved that the choice of tool chain would affect the verification efficiency [3]. Haxthausen and Fantechi studied the combined verification method of railway interlocking system, which provided reference for multi-subsystem modeling [4].

Research on real-time railway scheduling has gradually shifted from plan generation to operational state feedback. Versluis et al. studied the real-time railway traffic management framework under moving block conditions and pointed out that train operation needs to be modeled with signal state and capacity constraints [5]. D 'Amato et al. proposed the concept of self-organizing railway traffic management to make operation control coordinate according to local state changes [6]. Sharma et al. constructed a real-time traffic management method to maintain passenger continuity, demonstrating the value of constraint maintenance and conflict resolution [7]. de Weert et al. studied event request constraints in railway maintenance project scheduling and transformed operational requirements into model constraints [8]. Leutwiler et al. proposed a logical Benders decomposition method using delay similarity to accelerate railway rescheduling calculation [9]. Agasucci et al. used deep reinforcement learning to solve train scheduling tasks, which reflects the applicability of data-driven methods [10].

The above studies provide the basis for railway operation modeling, scheduling calculation and formal verification, but the hump unweaving process in marshalling station has strong discrete event characteristics. The shunting locomotive can only push the train in sequence, and the rolling result of the car is controlled by the HAC system, and it may enter the recovery branch after failure. The simple optimization model is difficult to express the probability attributes of "whether the state is reachable" and "whether the plan can be completed within a given time", and the ordinary simulation is difficult to give the confidence interval. Statistical model checking can run random trajectories in the semantics of timed automata, and express the completion rate, the failure state entry rate and the expectation of the number of rail cars with probabilistic queries, which is suitable for handling the task of planning reliability evaluation.

This paper focuses on the reliability evaluation of railway marshalling yard operation plan to construct a statistical model checking method. The train, shunting locomotive, main controller and hump signal system are abstracted as timed automata with stochastic time semantics, and the interarrival time, roll-off time and recovery time are parameterized by exponential distribution. The model describes events such as unmarshalling start, hump authorization, rollback success, rollback failure and recovery confirmation through synchronous channels, and completes probabilistic verification with Uppaal SMC. Research highlights include modeling of timed automata, reliability verification methods, and completion probability evaluation under perturbations.

The remaining parts are structured as follows: Section 2 introduces related research; In Section 3, the modeling of timed automata, the statistical model checking method and the completion probability evaluation model are given. Section 4 analyzes the conventional verification results and discusses the state evolution under perturbations of arrival and recovery rates. In Section 5, the conclusion is given.

2 Related work

This section presents research results related to modeling railway operation plans, scheduling algorithms, disturbance management, accident analysis, and simulation of shunting operations. The reliability evaluation of railway marshalling yard operation plan is not a single transportation organization calculation, but includes many discrete events such as train arrival, locomotive occupancy, hump roll, classified track access and fault recovery. The existing research provides a computational method basis for schedule modeling, real-time rescheduling, operation safety and shunting simulation, and also provides technical reference for introducing timed automata, probabilistic query and confidence interval estimation into statistical model checking.

Sartor et al. studied the mixed integer linear programming model of quasi-periodic strategic train timetable, and integrated the train interval, line capacity and period constraints into the optimization framework, which provided support for the computable expression of railway plans under discrete constraints [11]. Polinder et al. proposed an iterative train timetable heuristic algorithm for passenger centers, and embedded the adaptation time into the model solving process, so that the schedule evaluation changed from the pure operation time to the service response during operation [12]. Reynolds and Maher constructed a data-driven variable speed train schedule rescheduling model, and used operation data to describe the influence of speed changes on conflict resolution and delay propagation, indicating that data parameters can directly participate in the update of railway scheduling model [13].

Croella et al. studied the safe location assignment method in the disturbance management of railway system, and transformed the avoidance, parking and line occupancy of trains in abnormal scenarios into a solvable safe assignment model, which provided reference for the state transition control under uncertain operation [14]. Kloster et al. proposed a decision support tool for incremental train schedule based on optimization, so that the relationship between new trains and existing trains can be gradually adjusted through algorithm iteration. This idea has similar computational logic to the sequence constraints of subsequent trains waiting for the completion of sequence unweaving in the shunting station [15]. Bridgelall and Tolliver used machine learning and natural language processing to carry out railway accident analysis, and transformed unstructured accident texts into trainable features for identifying accident causes and risk categories, reflecting the data transformation ability of computational methods in railway safety assessment [16].

Mafokosi et al. established a system dynamics model of the impact of railway operation and maintenance on safety, availability, capacity and cost, and emphasized that operation and maintenance status would affect the overall performance of the system through the feedback chain, which is similar to the phenomenon that recovery time affects the completion probability of subsequent trains in hump disassembly [17]. Plissonneau et al. proposed a deep reinforcement learning method with prediction auxiliary task for autonomous train anti-collision control, which put the perception state, prediction information and action decision into a unified learning framework, and demonstrated the value of state evolution modeling in complex railway scenes [18]. Farrando et al. constructed a mathematical model of double-service hopping and stopping strategy considering demand-dependent stopping time, indicating that passenger demand, stopping time and operation plan can be expressed by explicit functional relationship [19].

Zien and Kirschstein proposed a rolling time domain method for shunting operations, and analyzed the operation effects of different shunting schemes through emission oriented simulation. This research is closer to marshalling yard operations, and its core lies in dividing the shunting task into local decision Windows that can be updated on a rolling basis, and using simulation to record the operation time, vehicle movement and resource occupancy changes [20]. Leutwiler and Corman studied the logical Benders decomposition method in microscopic railway timetable planning, divided the timetable into main level tasks and sub-level tasks, and used logical constraints to accelerate the solution, which provided a computational reference for the expression of microscopic constraints in railway operation planning [21]. Together, these studies show that the railway operation system has extended from the macroscopic timetable preparation to the microscopic state calculation, but the hump area of marshalling yard still needs to transform the start, roll, wait and resume in the operation chain into verifiable states.

From the perspective of method relationship, the research of schedule optimization focuses on the search of feasible scheme, the research of disturbance management focuses on the adjustment of train operation state, the research of safety analysis focuses on the identification of accident samples and risk factors, and the research of shunting simulation focuses on the resource occupation in the local operation window. The reliability evaluation concerned in this paper needs to further transform these computational objects into probabilistic attributes, so that the events such as whether the shunting locomotive is idle, whether the hump is occupied, whether the carriage is rolled successfully, and whether the recovery is completed can be put into a unified model checking process. In contrast to ordinary simulation, statistical model checking can also give confidence levels and error bounds so that each item completion probability has a reviewable statistical meaning. This expression is suitable to deal with multi-state synchronization and random time coupling in marshalling yard planning. And it can maintain the correspondence between the model structure and the verification results.

As shown in Table 1, existing studies have covered the direction of schedule modeling, rescheduling calculation, risk analysis and shunting simulation. However, these methods mostly focus on optimization objectives or operation performance, and less directly express verification attributes such as "whether the plan is completed within a given time bound", "what is the probability of failure state entry" and "how does the random recovery time change the completion probability of subsequent trains".

Table 1: Correspondence between related research methods and the task of this paper

Research Direction	Representative References	Main Computational Methods	Transferable Elements	Relation to This Study
Strategic and passenger-oriented timetabling	[11][12]	MILP, iterative heuristic	Discrete constraint representation, adaptation time handling	Supports plan parameter modeling and completion time modeling
Rescheduling and disruption management	[13][14][15]	Data-driven model, safe place assignment, incremental optimization	Delay propagation, abnormal state adjustment	Corresponds to arrival disturbance and recovery branch analysis
Safety and operational state analysis	[16][17][18]	Machine learning, system dynamics, deep reinforcement learning	Risk identification, feedback chain, state decision-making	Supports failure state modeling and reliability evaluation
Operation scheme and shunting simulation	[19][20][21]	Mathematical modeling, rolling horizon, logic-based Benders decomposition	Microscopic process, resource occupation, local decision-making	Corresponds to hump disassembly and shunting locomotive constraints

Hump operation in railway marshalling yards has the characteristics of strong synchronization, strong sequence and strong random. Trains, shunting locomotives, hump signaling systems and classified tracks need to be consistent through event triggering. Based on this, this paper formalizes the operation plan as a timed automata network with stochastic time semantics, and uses statistical model checking to verify the expected number of rail cars, the task failure probability and the train completion probability, thus forming a computerized evaluation method for the reliability of marshage station operation plan.

3 Research Methods

3.1 Temporal automata modeling of railway marshalling yard operation plan

The operation plan of railway marshalling yard has obvious discrete event characteristics. Train arrival, locomotive connecting, hump pushing, carriage rolling, switch and classified track access all occur in chronological order. In order to make the disassembly plan enter the computer verification environment, the job objects in the plan are abstracted as state entities, the job actions are abstracted as synchronous events, and the waiting, rollback and recovery processes are abstracted as state transitions with random delays. The model does not directly describe the manual scheduling text, but transforms the train plan into an executable automaton network, so that the subsequent reliability verification can be completed based on the state space.

Hump region operation process is the physical basis of automata modeling. The train is pushed from the receiving yard to the top of the hump by the shunting locomotive, and the carriages unhook and enter the target position through the reducer, the turnout and the classification track. The process involves a deviation between the actual and ideal position, which is too large to trigger a recovery operation or a failure branch. To clarify the subsequent modeling objects, this paper uses this process as the source of four types of entities: train, shunting locomotive, hump signaling system, and classified track, as shown in Fig. 1.

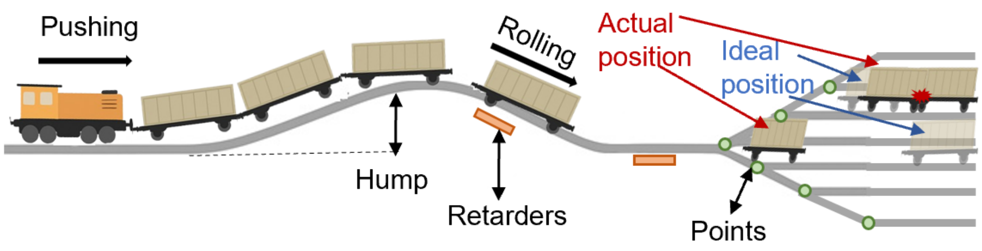

Figure 1: An illustration of the process of a train disassemble

To write the train arrivals, batch sizes, and classified track assignments in the unpacking plan as input vectors that can be read by the program while preserving the sequential execution relationship in the plan, the following equation is used:

$$P_i = (a_i, r_i, n_i, B_i, T_i), \quad B_i = \{b_{i1}, b_{i2}, \dots, b_{ik}\}, \quad T_i = \{\tau_{i1}, \tau_{i2}, \dots, \tau_{ik}\} \tag{1}$$

where P_i represents the input of the de-coding plan of the i train; a_i is the arrival time of the train. r_i denotes the track number of the receiving field; n_i represents the total number of carriages; B_i denotes the set of batches into which the train is divided; b_{ij} denotes the number of carriages in the j batch; T_i represents the target classification track set; Let τ_{ij}

denote the classified track corresponding to the j batch of cars. This formulation transforms the original operation plan into a structured input that can be easily read by the master controller automaton and distributed to the train automaton.

The hump signal system is the core of state judgment in the model. SignalInTheHump automata are used to describe states such as hump occupancy, roll-off authorization, roll-off check, successful put into orbit, failure recovery, and task failure. This automaton completes the probabilistic branch decision at the CheckSlip location, and enters the Success state if the rollback succeeds, and enters the Failed or MissionFailed state if the rollback fails. Its state transition structure is shown in Fig. 2.

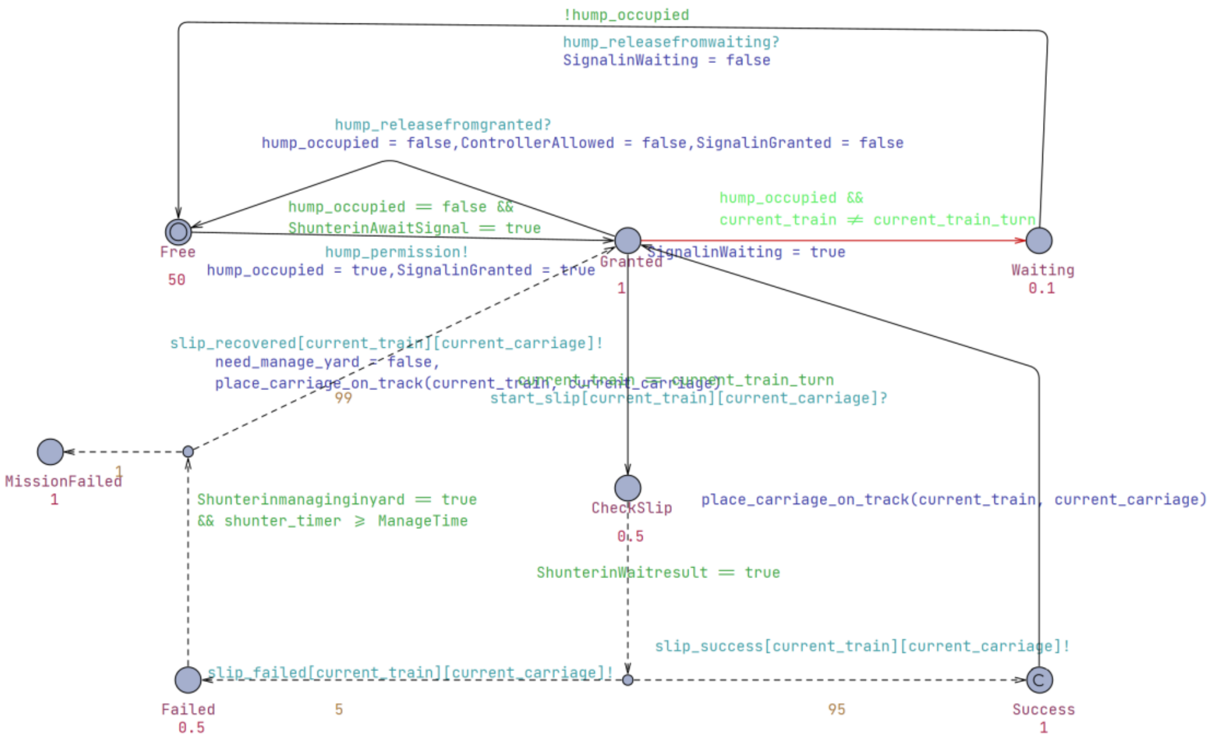

Figure 2: The SignalIntheHump automata of the train disassemble model

In order to uniformly represent the train, shunting locomotive, master controller and hump signal system into the same composable model, and to clarify the relationship between nodes, clocks and migration edges, the following equation is given:

$$A_m = (L_m, l_m^0, C_m, E_m, I_m, \Pi_m), \quad m \in \{C, T, S, H\} \tag{2}$$

Here, A_m denotes the m automaton; C, T, S and H denote the main controller, train, shunting locomotive and hump signaling system, respectively. L_m represents a finite set of states. l_m^0 represents the initial state; C_m represents the set of clock variables. E_m represents the set of state transition edges.I_m stands for state invariant. Let Π_m denote the set of internal parameters of the automaton. This formulation enables different operation entities to be modeled under a unified semantics, which is convenient for subsequent combination into a complete network through synchronous channels.

The master controller is responsible for converting the disassembly plan into sequential start events. The MainController automaton enters PreStartNo_1, PreStartNo_2, and PreStartNo_3 from the Beginning state and triggers the disassemble process of the three trains in turn through the start_disassemble[i] channel. The control structure guarantees that the train will not enter the hump area in advance when it does not arrive or does not have the operating conditions, as shown in Fig. 3.

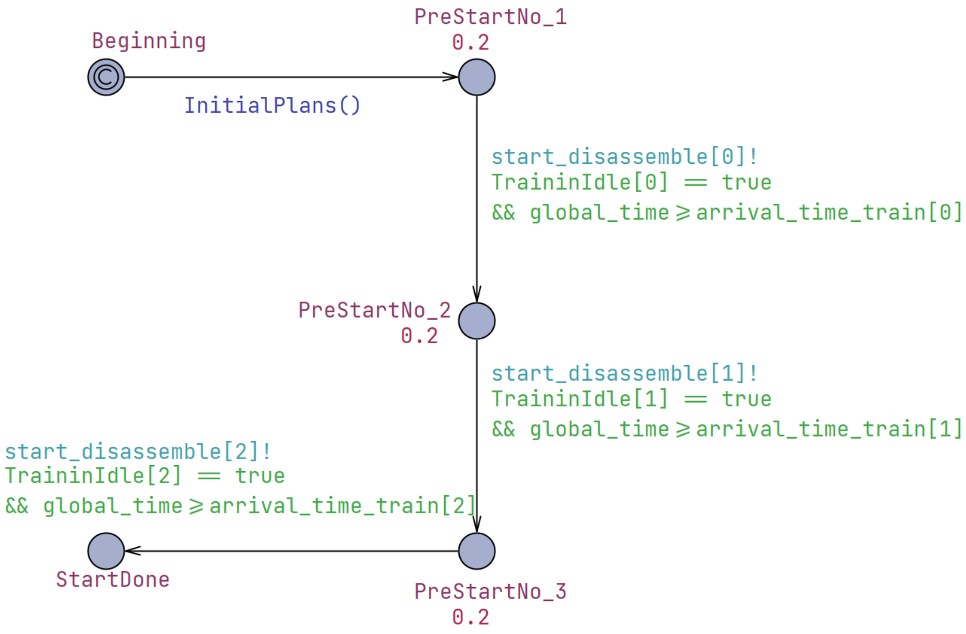

Figure 3: The MainController automata of the train disassemble model

In order to describe the state update process of a certain transition edge when the guard condition, synchronization event and clock reset are satisfied at the same time, and make the automaton transition identifiable by the verification tool, the following equation is given:

$$(l, v) \xrightarrow{g \wedge ch,\ R} (l', v') \quad \text{if} \quad v \models g,\ \text{sync}(ch) = 1,\ v' = \text{Reset}(v, R) \tag{3}$$

Here, l and l' denote the state of the automaton before and after the transition, respectively. v represents the clock estimate before migration. v' represents the migrated clock valuation; g denotes the protection condition; ch stands for synchronization channel; $\text{sync}(ch) = 1$ means that the sender and receiver synchronized successfully; R denotes the set of clocks to be reset. $\text{Reset}(v, R)$ indicates that the new valuation will be specified after the clock is reset. This formulation is used to describe a valid state transition in the model so that train start, hump authorization, and roll-off results can all be performed in a formal manner.

Through the above modeling, the disassembly plan is no longer just a static job table, but is transformed into a runnable network of stochastic timed automata. The master controller saves the plan sequence, the train automaton saves the batch release process, the shunting locomotive automaton saves the resource occupancy and return process, and the hump signal automaton saves the roll-off authorization and failure recovery judgment. Different automata are connected by synchronous events, and state transitions are controlled by clock constraints and guard conditions. This modeling method provides an executable state space for the subsequent statistical model checking, and enables the plan reliability to be verified from empirical judgment to computational verification.

3.2 Plan reliability verification method based on statistical model checking

Statistical model checking is used to execute a large number of simulation trajectories on a network of stochastic timed automata and compute property satisfaction probabilities based on statistical inference. Different from ordinary simulation which only outputs a number of paths, SMC defines the verification goal as a temporal logic property, and determines whether a state can be reached within a given time bound by probabilistic query. In this paper, marshage station operation plan reliability is transformed into three types of attributes: expectation of number of classified rail cars, task failure probability and train completion probability. The verification process is done by Uppaal SMC and the channel semantics in the model are shown in Table 2.

Table 2: Synchronization channels and their operational semantics in the UPPAAL model

Channel	Sender → Receiver	Meaning
start_disassemble[i]	MainController! → Train(i)?	Controller activates disassemble starting signal of train i.
request_slip	Shunter! → SignalInTheHump?	Request to initiate carriage slip at hump.
hump_permission	SignalInTheHump! → Shunter?	Grants exclusive access to the hump section, ensuring signaling principle.
start_slip[i][j]	Shunter! → SignalInTheHump?; Shunter! → Train(i)?	Initiates the rolling of the j-th batch from train i.
slip_success[i][j]	SignalInTheHump! → Shunter?	Indicates successful release.
slip_failed[i][j]	SignalInTheHump! → Shunter?	Reports a failed release, such as overrun or misalignment.
slip_recovered[i][j]	Shunter! → SignalInTheHump?	Acknowledges recovery from failure; normal operation resumes.
release_slip	Shunter! → SignalInTheHump?	Notifies that the shunter has completed its current release cycle.
hump_release	SignalInTheHump! → Shunter?	Releases hump occupancy; enables the next queued operation.

In order to write the state transition, time delay and probability branch in a complete simulation trajectory as path probability, and serve as the sampling basis for statistical model checking, the following equation is shown:

$$\mathbb{P}(\omega) = \prod_{q=1}^{Q} \left[p_q \cdot f_q(\Delta t_q)\right] \tag{4}$$

Here, ω represents a simulation trajectory; Q denotes the number of state transitions in this trajectory; p_q denotes the discrete probability branch corresponding to the q migration, such as the roll-off success or failure probability. $f_q(\Delta t_q)$ denotes the probability density function of the q state residence time Δt_q. This formulation is used to describe the sources of probabilities for paths of stochastic timed automata, enabling both discrete events and continuous-time delays to participate in reliability computation.

In order to calculate the probability of completion of the Train plan within a given time bound, and to enable the completion state to directly correspond to the Done position in the Train automaton, the following equation is given:

$$\widehat{P}_{done}(T) = \frac{1}{N_s}\sum_{s=1}^{N_s} 1\,(\exists t \le T:\ \mathrm{Train}(k).\mathrm{Done}_s(t) = 1) \tag{5}$$

Here, $\widehat{P}_{done}(T)$ is the estimated probability of completing all the plans within the time bound T. N_s represents the number of simulation trajectories; $1(\cdot)$ is an indicator function; $\mathrm{Train}(k).\mathrm{Done}_s(t)$ indicates whether the last train in the s trajectory reaches the completed state at time t. The formula transforms "plan completion" into state reachability events, which is suitable for evaluating the overall completion probability of multi-train sequential unpacking tasks.

In order to describe the expectation of the number of cars received by the classified track within a limited time and incorporate the track count variable into the verification target, the following equation is shown:

$$\widehat{E}_{track}(T) = \frac{1}{N_s}\sum_{s=1}^{N_s} \max_{0\le t\le T} \mathrm{Count}_r^s(t) \tag{6}$$

Here, $\widehat{E}_{track}(T)$ represents the sample expectation of the maximum number of classified rail cars in item r within time bound T. $\mathrm{Count}_r^s(t)$ is the number of cars in track rr in track s at time t. max is used to take the maximum number of carriages reached by this trajectory within the time limit. This formula is used to verify whether the classified track throughput status matches the planned allocation and can reflect the cumulative track effect after batch roll-off.

In order to give the statistical error range of the probability estimation results, and make the completion probability and failure probability have reviewable confidence intervals, the following equation is shown:

$$CI_\alpha = \hat{p} \pm z_{\alpha/2}\sqrt{\frac{\hat{p}(1-\hat{p})}{N_s}} \tag{7}$$

Here, CI_α denotes the interval with confidence level $1-\alpha$. $\hat{p}$ represents the estimated probability value obtained from the simulation samples. $z_{\alpha/2}$ is the standard normal distribution quantile. N_s denotes the number of sample trajectories. This formulation is used to give statistical bounds on probabilistic query results, so that the model output is not just a single numerical value, but a reliability estimate with a margin of error.

To quantify the probability of entering the unrecoverable failure state of the disassembly scheme, and consider the MissionFailed position in the SignalInTheHump automaton as the risk event, the following equation is given:

$$\widehat{R}_{fail}(T) = \frac{1}{N_s}\sum_{s=1}^{N_s} 1\,(\exists t \le T:\ \mathrm{MissionFailed}_s(t) = 1) \tag{8}$$

Here, $\widehat{R}_{fail}(T)$ represents the probability estimate of entering an unrecoverable failure state within the time bound T. $\mathrm{MissionFailed}_s(t)$ indicates whether the s trajectory entered the mission failure state at time t. This formulation corresponds directly to the failure branch in the hump signal automaton and is able to measure the impact of rollback failures, recovery failures, and resource unavailability on plan reliability.

Thus, plan reliability verification shifts from single simulation results to multi-path statistical judgment. The synchronization channel ensures that the communication between the main controller, the train, the shunting locomotive, and the hump signal system is completed in a sequence of events, and the status query converts plan completions, track counts, and failed entries into computable results. The verification process can simultaneously output the completion probability, the expectation of the number of carriages and the confidence interval, so that the reliability of the disassembly plan no longer depends on the experience judgment, but is supported by the reachable model operation results. This method retains the temporal logic constraints and also retains the error bounds in the random running process, which can provide a unified data source for the completion probability curve, failure probability distribution and track count changes in subsequent experiments.

3.3 Operation plan completion probability evaluation module for uncertain disturbance

The execution result of marshalling yard operation plan is affected by train arrival interval, return time of shunting locomotive, rolling state of carriages and failure recovery process. In order to evaluate the effect of these disturbances on the completion probability of the plan, this paper introduces a disturbance parameter layer based on the original timed automata network, and takes the arrival rate, roll-off success rate and recovery rate as adjustable parameters, and obtains the completion probability changes through multiple rounds of SMC simulation. The model does not change the automaton structure, only the random time parameters and probabilistic branches, so as to ensure the comparability between different experimental results.

The disturbance evaluation process includes five computational stages: plan input, parameter perturbation, automaton simulation, probabilistic query and reliability output. Plan input comes from train arrival time and batch allocation, parameter perturbation acts on the main controller and hump signal system, simulation phase generates random execution traces, probability query phase calculates completion rate, failure rate and state occupancy time, and output phase forms evaluation results oriented to plan reliability, as shown in Fig. 4.

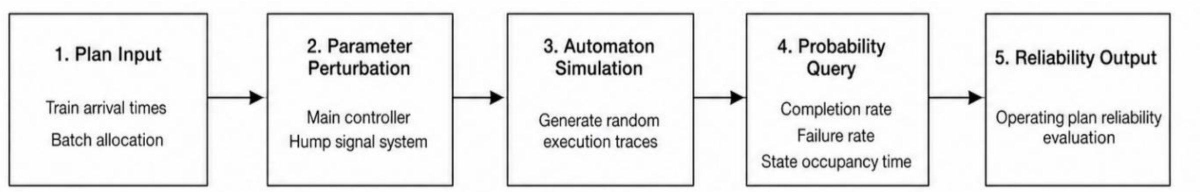

Figure 4: Flowchart of evaluation of completion probability of operation plan under uncertain disturbance

In order to describe the randomness of the train arrival interval and transform the dwell time of the PreStartNo state in the main controller into an adjustable probability parameter, the following equation is shown:

$$f_{arr}(\Delta t; \lambda_a) = \lambda_a e^{-\lambda_a \Delta t}, \quad \Delta t \geq 0 \tag{9}$$

where $f_{arr}(\Delta t; \lambda_a)$ represents the probability density function when the train arrival interval obeyed the exponential distribution. Δt represents the time interval between the start of adjacent trains; Let λ_a denote the arrival rate parameter. This formula is used to describe the influence of arrival disturbance on the state transition of the main controller. The larger λ_a is, the faster the train starting condition is satisfied. The smaller λ_a is, the longer the intermediate waiting state lasts.

In order to describe the impact of failure recovery time on the plan completion process, and incorporate the randomness of the time when the failed branch returns to the normal job chain into the model, the following equation is given:

$$f_{rec}(\theta;\lambda_r) = \lambda_r e^{-\lambda_r \theta}, \quad \theta \geq 0 \tag{10}$$

where $f_{rec}(\theta;\lambda_r)$ represents the probability density function of the recovery time θ. Let λ_r denote the recovery rate parameter. This formula corresponds to the recovery branch of SignalInTheHump automaton. The higher the recovery rate is, the shorter the dwell time of failure state is. The lower the recovery rate, the more likely the fault trajectory is to remain in the shunting locomotive and hump occupancy state, thus affecting the subsequent train start.

In order to measure the influence strength of disturbance parameter changes on plan completion probability and compare the sensitivity of reliability output under different parameter groups, the following equation is given:

$$S_\lambda = \frac{\hat{P}_{done}(T|\lambda + \Delta\lambda) - \hat{P}_{done}(T|\lambda)}{\Delta\lambda} \tag{11}$$

Here, S_λ represents the local sensitivity of the completion probability to the perturbation parameter λ. $\hat{P}_{done}(T|\lambda + \Delta\lambda)$ is the probability of completion within a time bound T for a parameter λ. $\Delta\lambda$ represents the parameter perturbation amplitude. The formula is used to compare the direction and magnitude of the impact of parameters such as arrival rate and recovery rate on the completion probability, which provides a calculation basis for disturbance analysis.

In order to comprehensively express the joint influence of completion probability, failure probability and average completion time on plan reliability, and avoid judging plan quality only by a single index, the following equation is shown:

$$\Gamma(T) = \eta_1 \hat{P}_{done}(T) - \eta_2 \hat{R}_{fail}(T) - \eta_3 \frac{\hat{D}(T)}{T} \tag{12}$$

where $\Gamma(T)$ represents the comprehensive reliability score under time bound T. η_1 to η_3 represent the weight coefficients; $\hat{P}_{done}(T)$ is the probability of plan completion. $\hat{R}_{fail}(T)$ is the probability of failure. $\hat{D}(T)$ denotes the average completion time or delay time. The formula compares plan completion, failure risk and time consumption at the same scale, and is suitable for comprehensive evaluation of different disturbance scenarios.

In order to describe the least favorable completion probability in the set of disturbance scenarios and ensure that the reliability evaluation covers the operating boundary under multiple sets of parameter combinations, the following equation is given:

$$P_{rob}(T) = \min_{\lambda_a \in \Lambda_a, \lambda_r \in \Lambda_r, p_s \in \Omega_s} \hat{P}_{done}(T|\lambda_a, \lambda_r, p_s) \tag{13}$$

Here, $P_{rob}(T)$ represents the robust completion probability within the set of perturbed parameters. Λ_a denotes the set of arrival rate values; Λ_r represents the set of recovery rate values. Let Ω_s denote the set of roll-off success probabilities; p_s denotes the single-roll success probability. The formula is used to identify the lower bound of the plan completion probability under the condition of multiple disturbances, so that the evaluation results not only reflect the conventional scenario, but also cover the combination of low arrival rate, low recovery rate and increased roll-off deviation.

After the above design, the operation plan completion probability evaluation model forms a complete calculation chain from disturbance input to reliability output. The arrival rate affects the starting and waiting process of the main controller, the recovery rate affects the fault back-off process of the hump signal automaton, and the roll-off success rate affects the state result of the carriage entering the classified track. The model is able to adjust the stochastic parameters without changing the job structure and observe the changes in completion probability, failure risk, and state time consumption. In this way, it can not only maintain the correspondence between the experimental results and the state of the automaton, but also reflect the difference of the plan reliability under different operating conditions, which provides a direct basis for the subsequent routine plan verification and disturbance condition analysis.

4 Results and analysis

4.1 Experimental hump configuration and disassembly plan parameter setting

The experiment uses a typical hump railway marshalling yard as the verification scene, and the operation area is composed of a receiving yard, a hump area, a sorting yard, a shunting locomotive and a hump automatic control system. After arriving at the receiving yard, the train is attached and pushed to the top of the hump by the shunting locomotive, and the carriages are unhooked and rolled to the designated classification track by gravity. In order to describe the resource occupancy relationship in the statistical model checking environment, the experiment is set up in single cart and single roll mode, and only one shunting locomotive is allowed to perform the disassembly task at a time. After the previous train completes the main disassembly process, the shunting locomotive returns to the receiving field, and then connects with the next train to be disassembly, forming a sequential operation chain.

In the Uppaal SMC model, the unmarshalling schedule parameters are written into the master controller automaton, including train arrival time, receiving field track, number of cars, number of batches, and target classification track. Train automata record arrival, push, roll, wait and finish states. Shunting locomotive automata describe the process of connecting, pushing, returning and fault recovery. The hump signaling automaton determines hump occupancy, roll-off authorization, roll-off success, and task failure status. The average roll-off time, locomotive return time, signal waiting time and recovery time are represented by exponential distribution, which is used to describe the uneven arrival interval, rolling deviation of carriages and the fluctuation of recovery operation time.

As shown in Table 3, a total of three inbound trains are set up in the experiment, and the size of the carriages is 15, 12 and 20, respectively, and the corresponding number of batches is 3, 2 and 5. Train 1 enters reception yard lane 2 at 08:00, Train 2 enters reception yard lane 4 at 09:40 and train 3 enters reception yard lane 1 at 10:30. Each batch of carriages is allocated to five classified tracks according to the disassembly plan, forming a continuous sequential operation process. The configuration can reflect the operation characteristics of resource exclusive, batch roll off, track allocation and fault recovery under the condition of a single shunting locomotive, and it is also easy to observe the influence of train arrival interval, batch number and classified track occupancy on plan completion probability. The experimental output includes the expected value of the number of classified rail cars, the waiting time of shunting locomotives, the task failure probability and the state time occupancy distribution, and is input into the attribute verification module uniformly to establish the corresponding relationship with the time bound, failure state and track count variables, which provides the data basis for subsequent probability query and confidence interval calculation.

Table 3: Plan of train uncoding scheme

Train No.	Arrival Time	Receiving Yard Track (Number of Carriages)	Number of Batches	Target Classification Tracks (Number of Carriages)
1	08:00	2 (15+)	3	1 (5−); 2 (4−); 3 (6−)
2	09:40	4 (12+)	2	4 (6−); 5 (6−)
3	10:30	1 (20+)	5	1 (2−); 2 (4−); 3 (5−); 4 (3−); 5 (6−)

4.2 Disassembly plan routine verification results and task completion probability analysis

In this section, statistical model checking is performed on the conventional execution state of three incoming trains based on the hump configuration and de-codition plan presented in the previous section. The model input includes Train arrival time, receiving field track, number of carriages, number of batches and target classification track, and the master controller automaton triggers the operation process of Train(0), Train(1) and train (2) in order of disassembly. Uppaal SMC generates multiple execution paths under random-time semantics and performs probabilistic queries on track count variables, failure states, and train completion locations. This section does not adjust the arrival and recovery rates, and only observes the plan execution results under the original parameters, which are used to form a benchmark for subsequent perturbation analysis. In order to observe the accumulation of carriages of the classified track in a limited time, the model uses E[<=200;2000] (max:track_car_count[1]) as the expected query attribute to count the maximum number of carriages that can be reached by track 1 in 200 minutes. The query is not the result of a single run, but is formed by calculating the maximum value of the track count variable in multiple random simulation paths.

As shown in Fig. 5, the expected number of cars in track 1 in 200 minutes is concentrated around 6.5 cars. This result indicates that the five cars assigned to track 1 in train 1 have completed the main roll, and some cars entering track 1 in train 3 have started to participate in counting, but have not yet fully stabilized to the final seven-car state. Because the shunting locomotive adopts the sequential operation mode, the carriages of train 3 need to wait for the previous sequence cars to complete the push and return process when entering track 1, so the count of track 1 is in a phased transition state at 200 minutes. The distribution can reflect the classified track throughput capacity of the original plan within the time limit.

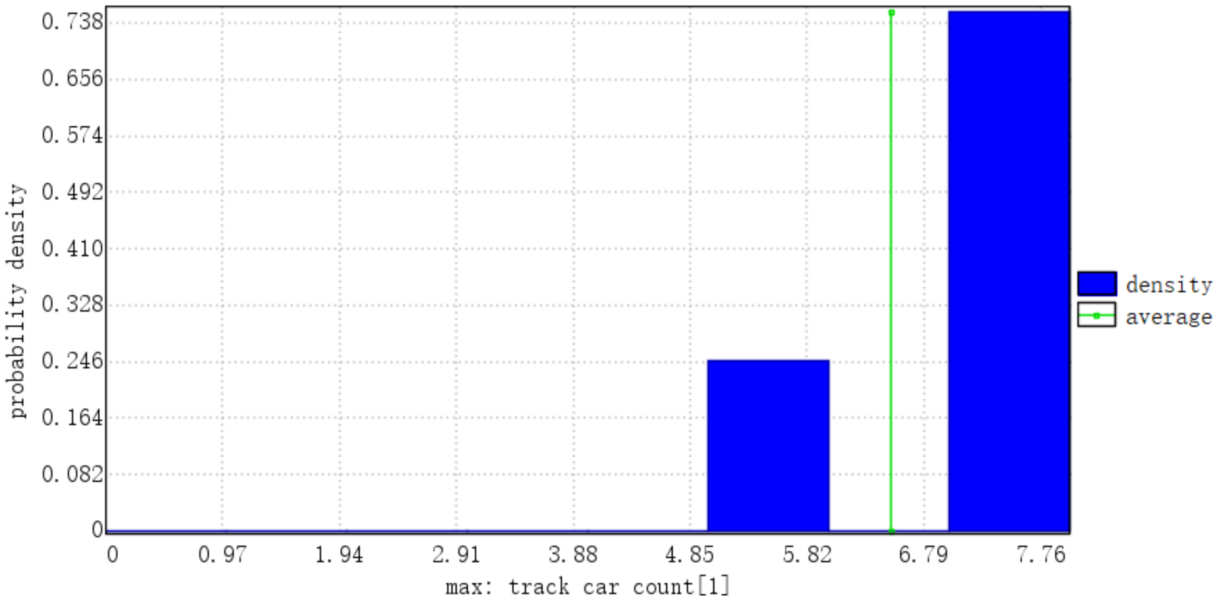

Figure 5: The probability distribution of the number of carriages expectations within 200 minutes

As shown in Fig. 6, the number of carriages in track 1 converges from 5 to 7 as the simulation time advances. According to the disassembly plan in Table 3, train 1 allocates 5 cars to track 1, train 3 adds 2 cars to track 1, and the cumulative number of cars in track 1 should be 7 after the completion of the plan. As train 3 gradually enters the roll-off stage, the state probability of 5 cars continues to decrease, the state probability of 7 cars continues to increase, and the average number of cars gradually approaches 7 cars from around 5 cars. This change indicates that the track_car_count[1] variable in the model can correctly record the batch roll-off results, and the track count change is consistent with the unpacking plan。

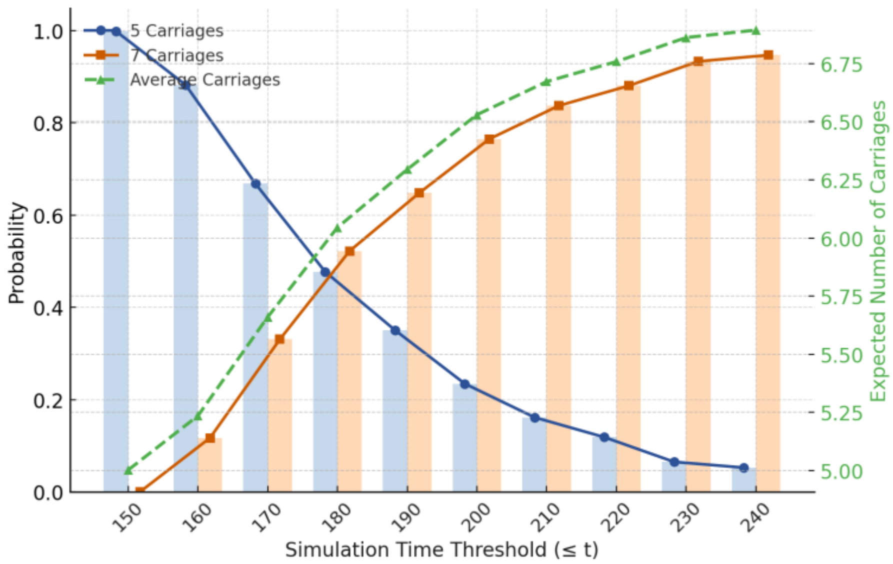

Figure 6: The expectations of number of carriages in track 1

After completing the track count verification, the model further performs probabilistic queries on unrecoverable failure states. This state is triggered by the failure position in the SignalInTheHump automaton and mainly corresponds to the situation that recovery cannot be completed after the failure of the carriage roll and drop. Since each train has roll success, roll failure and recovery judgments in the hump release process, the failure probability will change in stages with the entry of different train batches.

As shown in Fig. 7, the probability of unrecoverable failure of the uncoding scheme is 0.48%±0.01%, the confidence level is 95%, and the number of simulations reaches 1 million. There are three obvious peaks in the probability density curve, corresponding to the uncoding time Windows of the three trains. This result indicates that the failure risk is not uniformly distributed throughout the operation cycle, but is concentrated at the stage when each train enters hump roll and recovery judgment. The overall failure probability is low, indicating that under the current HAC roll-off success rate and recovery branch setting, the original disassembly plan has high executability, but the failure state still affects the start time of the subsequent train.

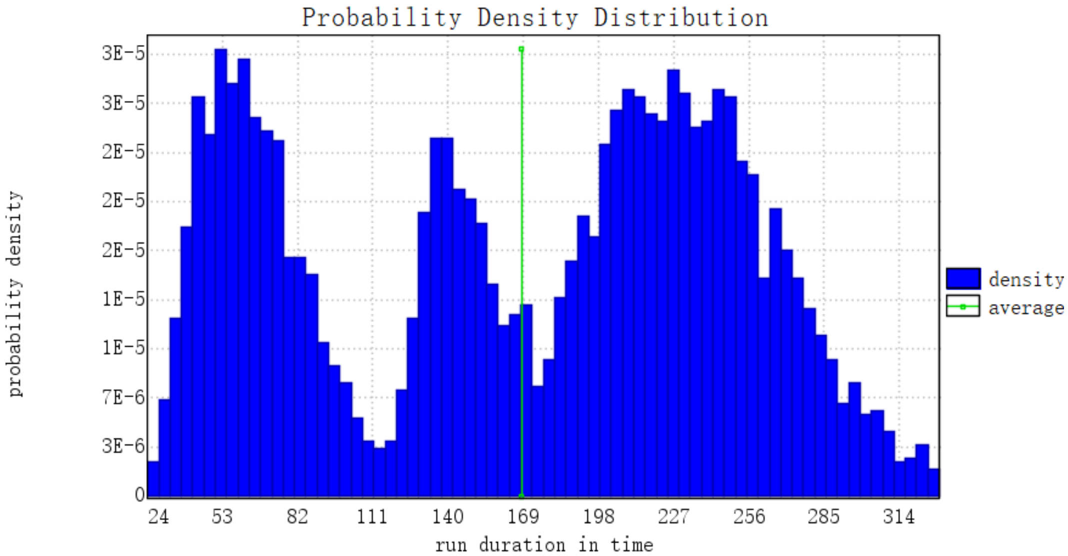

Figure 7: The probability distribution of the failure (cannot be recovered) of the disassemble plan

In order to test whether all the plans can be completed within the specified time, the model takes the completion positions of Train(0), Train(1) and Train(2) as the query objects, and statistics the completion probability under different time bounds T. Since the three trains share the same shunting locomotive, the subsequent trains must wait for the previous sequence car to complete the main disassembly process before starting, so the three completion probability curves show obvious sequence differences.

As shown in Fig. 8, the completion probability of train (0) rises the earliest, increases rapidly after 60 minutes, and stabilizes above 0.99 after 150 minutes. Train (1) starts to increase significantly after 120 minutes and enters the high completion probability interval after 240 minutes. The completion probability of train (2) rises the slowest, reaching 0.9558 at 330 minutes, because it contains five rolling batches. This change is consistent with the batch number relationship in Table 3, which also indicates that the single shunting locomotive and the sequential starting mechanism form a clear time dependence in the model.

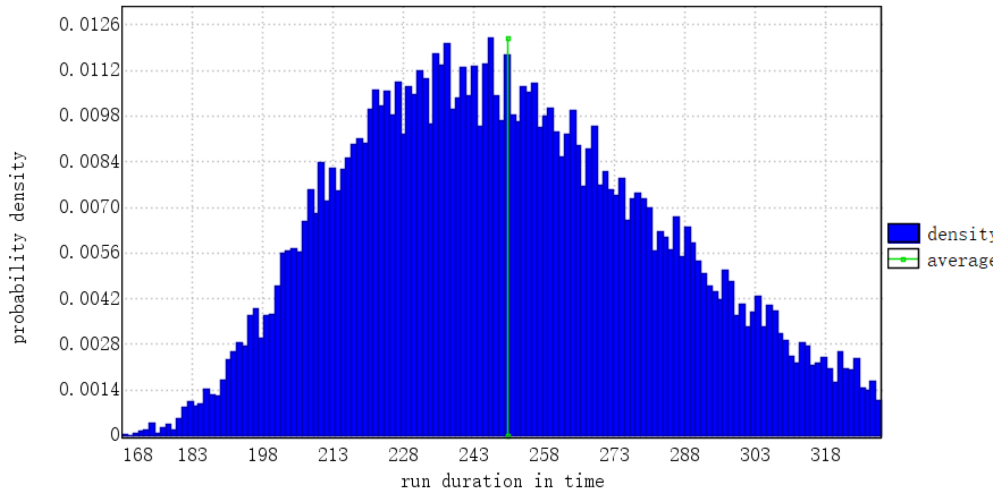

Figure 8: Completion probability of Train(0)–Train(2) with Uppaal SMC confidence intervals

As can be seen from Table 4, the completion probability of train (0) reaches 0.9676 at 120 minutes, indicating that the first train is mainly affected by its own three rolling batches. The completion probability of train (1) is 0.5944 at 150 minutes and increases to 0.9738 at 210 minutes, which reflects the starting delay caused by the return and re-connecting of the shunting locomotive after the completion of the previous train. Train (2) is only 0.1055 at 210 minutes, rises to 0.6994 at 270 minutes, and reaches 0.9558 at 330 minutes, indicating that the tail train simultaneously accepts the random fluctuation caused by the previous waiting time and its own five batches. The narrow confidence intervals in Table 4 indicate that the statistical sample size can support stable probability estimates.

Table 4: Completion probability with confidence intervals for Train(0)–Train(2)

Time T (min)	Train(0) Estimate	Train(0) CI(95%)	Train(1) Estimate	Train(1) CI(95%)	Train(2) Estimate	Train(2) CI(95%)
60	0.4938	[0.4868, 0.5007]	$\leq$ 0.0002	[-, -]	$\leq$ 0.0002	[-, -]
90	0.8450	[0.8400, 0.8500]	$\leq$ 0.0002	[-, -]	$\leq$ 0.0002	[-, -]
120	0.9676	[0.9648, 0.9698]	0.0646	[0.0612, 0.0681]	$\leq$ 0.0002	[-, -]
150	$\geq$ 0.99	[0.9913, 0.9937]	0.5944	[0.5876, 0.6012]	$\leq$ 0.0002	[-, -]
180	$\geq$ 0.99	[0.9971, 0.9984]	0.8875	[0.8831, 0.8919]	0.0018	[0.0012, 0.0025]
210	$\geq$ 0.99	[0.9976, 0.9988]	0.9738	[0.9716, 0.9761]	0.1055	[0.1012, 0.1098]
240	$\geq$ 0.99	[0.9980, 0.9991]	$\geq$ 0.99	[0.9919, 0.9942]	0.3994	[0.3926, 0.4062]
270	$\geq$ 0.99	[0.9980, 0.9991]	$\geq$ 0.99	[0.9919, 0.9942]	0.6994	[0.6930, 0.7058]
300	$\geq$ 0.99	[0.9980, 0.9991]	$\geq$ 0.99	[0.9919, 0.9942]	0.8763	[0.8718, 0.8808]
330	$\geq$ 0.99	[0.9980, 0.9991]	$\geq$ 0.99	[0.9966, 0.9981]	0.9558	[0.9529, 0.9587]

Based on the above, it can be seen that the conventional unpacking plan has a high completion probability within the time limit of 330 minutes, the change of the number of carriages in track 1 is consistent with the batch allocation, and the unrecoverable failure probability is at a low level. The completion probability of train (2) rises the slowest, which indicates that the tail train is the main observation object in the conventional reliability verification. The results in this section show that the statistical model checking can unify the track count, failure state and train completion state into the state space of the query automaton, which provides a benchmark for the subsequent analysis of the state evolution under the disturbance of arrival rate and recovery rate.

4.3 State evolution and reliability analysis under perturbation of arrival and recovery rates

Based on the conventional verification results, this section further analyzes the impact of changes in train arrival rate and fault recovery rate on plan reliability. The main controller, train, shunting locomotive and hump signal automata are kept unchanged in the model structure, and only the random time parameter is adjusted, so that the difference of results can directly correspond to the arrival disturbance and recovery disturbance. The arrival rate mainly affects the dwell time of the PreStartNo state in the MainController automaton, and the recovery rate mainly affects the speed of the failed branch back to the normal job chain in the SignalInTheHump automaton.

As shown in Fig. 9, the completion probability of train 3 has a clear lag characteristic. Train 3 contains five roll and release batches, which is the object with the largest number of batches among the three trains. Its completion probability is almost zero before 180 minutes, and starts to rise after 210 minutes, reaching 0.6994 at 270 minutes, 0.8763 at 300 minutes, and 0.9558 at 330 minutes. The curve shows that the completion state of the last train is not only affected by its own batch number, but also constrained by the completion time of train (0), train (1) and the return process of shunting locomotive.

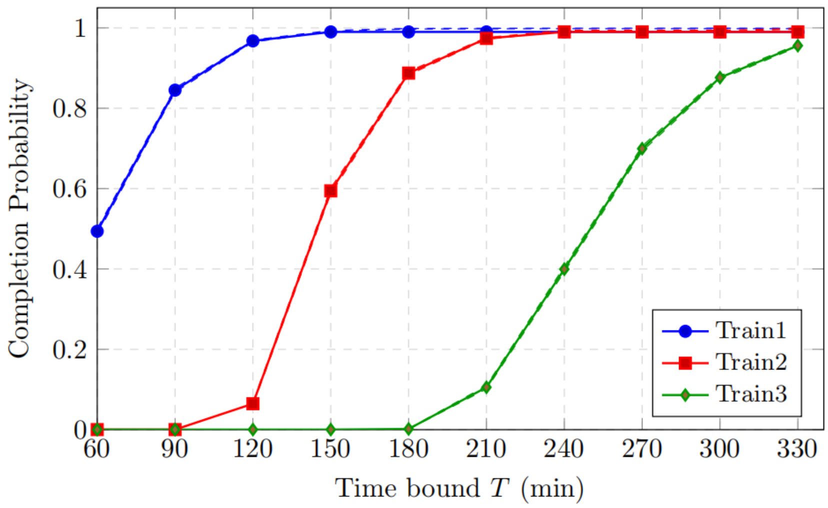

Figure 9: The probability distribution of fulfillment for the disassemble of train 3

As shown in Fig. 10, the MainController automaton successively passes through the states Beginning, PreStartNo_1, PreStartNo_2, PreStartNo_3, and StartDone in one simulation. The state changes unfold in steps, which indicates that the controller does not start three trains at the same time, but gradually sends out the start signal according to the global time, the train ready mark and the resource occupancy of the shunting locomotive. PreStartNo_1 corresponds to train 1 starting preparation, PreStartNo_2 corresponds to train 2 waiting to start, and PreStartNo_3 corresponds to the wait before train 3 enters the job chain.

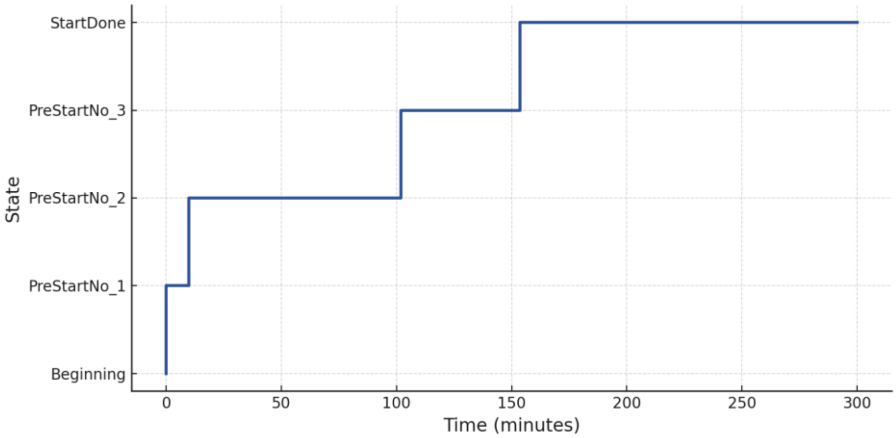

Figure 10: Time elapsed in MainController with one simulation

After completing the single state time-consuming observation, the model further adjusted the train arrival rate parameter, which was used to compare the influence of different arrival distributions on the state occupancy probability of the main controller. The higher the arrival rate, the faster the controller satisfies the train starting condition. The lower the arrival rate is, the longer the dwell time of the intermediate state will be, and the start window of the subsequent train will be delayed.

As shown in Fig. 11, under the high arrival rate scenario λ=20, the main controller leaves the PreStartNo_1 and enters the subsequent state faster, and the state occupancy probability completes the transition within a short time window. In contrast, under the low arrival rate scenario λ=0.2, the probability mass stays longer in the PreStartNo_2 to PreStartNo_3 region, the state transition is more scattered, and the time for the system to enter the StartDone state is delayed. This result shows that the arrival rate does not only change the initial firing time of a certain train, but also affects the occupancy distribution of subsequent trains in the state space of the automaton, and further changes the convergence rate of the task completion probability.

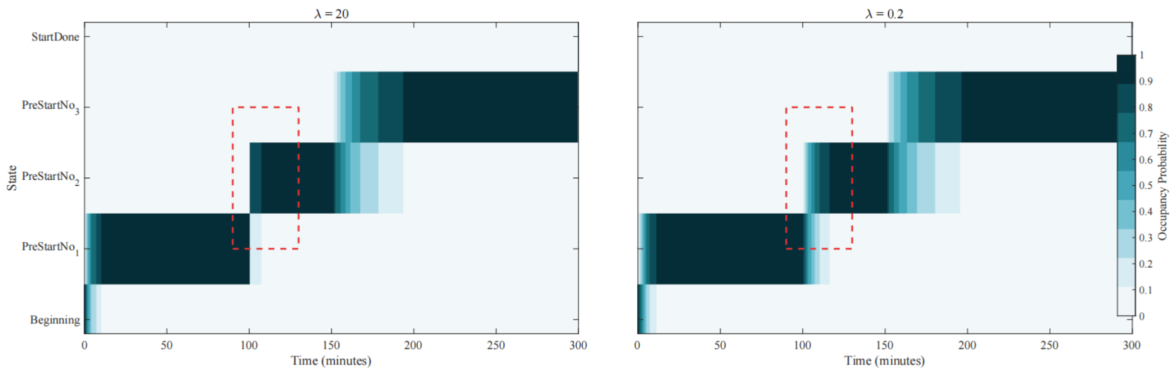

Figure 11: Comparison between different arrival rate of train 2 (20 and 0.2)

As shown in Fig. 12, when the recovery rate λ=50, the completion probability curve of the train enters the stable interval faster as a whole. When the recovery rate λ=0.05, the overall curve shifts backward, especially in train (2). In the early stage, the difference between the two sets of curves is small; train (0) dominates the operation progress before T=120 minutes, and train (1) and train (2) have not yet fully entered the completion interval. After T=180 minutes, the high recovery rate and low recovery rate scenarios start to diverge, indicating that the recovery branch has a persistent impact on plan tail reliability.

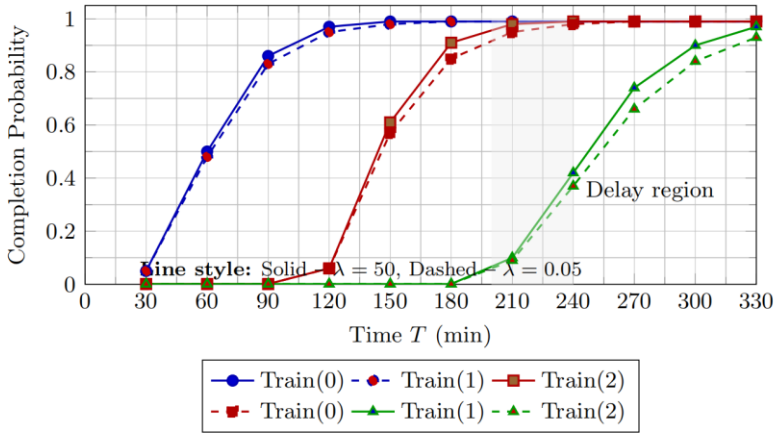

Figure 12: Comparison of completion probabilities for Train(0)–Train(2) under two recovery rates. Solid lines represent λ = 50, dashed lines represent λ = 0.05. Blue, red, and green correspond to Train(0), Train(1), and Train(2), respectively.

From Table 5, it can be seen that the recovery rate change has a small impact on the early completion probability of train (0), but it has a more obvious impact on the later completion probability of train (1) and train (2). When λ=50, the completion probability of train (2) is 0.74 in 270 minutes and 0.97 in 330 minutes. When λ=0.05, train (2) is 0.66 at 270 minutes and 0.93 at 330 minutes. This difference indicates that the time delay of the recovery process will be passed backward along the sequential job chain, and the tail train is more susceptible to the decrease of recovery efficiency. The lower the recovery rate, the longer it takes for the failed branch to return to the normal operation chain, and the longer the shunting locomotive and hump resources are occupied。

Table 5: Comparison of completion probabilities for Train(0)–Train(2) under different recovery rates (λ)

Time	λ = 50 Train(0)	λ = 50 Train(1)	λ = 50 Train(2)	λ = 0.05 Train(0)	λ = 0.05 Train(1)	λ = 0.05 Train(2)
30	0.05	≤0.001	≤0.001	0.05	≤0.001	≤0.001
60	0.5	≤0.001	≤0.001	0.48	≤0.001	≤0.001
90	0.86	≤0.001	≤0.001	0.83	≤0.001	≤0.001
120	0.97	0.06	≤0.001	0.95	0.06	≤0.001
150	≥0.99	0.61	≤0.001	0.98	0.57	≤0.001
180	≥0.99	0.91	≤0.001	≥0.99	0.85	≤0.001
210	≥0.99	0.98	0.10	≥0.99	0.95	0.09
240	≥0.99	≥0.99	0.42	≥0.99	0.98	0.37
270	≥0.99	≥0.99	0.74	≥0.99	≥0.99	0.66
300	≥0.99	≥0.99	0.90	≥0.99	≥0.99	0.84
330	≥0.99	≥0.99	0.97	≥0.99	≥0.99	0.93

To further judge the contribution of different components in the model to the reliability verification results, the supplementary setup ablation experiment is shown in Table 6.

Table 6: Results of ablation experiments for the reliability validation model

Model Setting	Completion Probability at 330 min	Mission Failure Probability/%	Average Completion Time/min	95% CI Width	Result Description
Complete model	0.9558	0.48	246.3	0.0058	Preserves complete stochastic timing and resource constraints
Without arrival-rate stochastic term	0.9721	0.45	238.6	0.0049	Arrival disturbance is weakened, and the completion probability increases
Without recovery-rate stochastic term	0.9314	0.71	259.8	0.0075	The recovery process is weakened, and tail-end delay expands
Without failure transition	0.9865	0.00	232.4	0.0038	Failure risk is underestimated, leading to an inflated reliability result
Without exclusive shunting-locomotive constraint	0.9912	0.31	218.7	0.0041	Parallel operation capacity is overestimated, which is inconsistent with actual operations
Without confidence interval estimation	0.9558	0.48	246.3	—	Only point estimates are obtained, without statistical error boundaries

Table 6 shows that the 330-minute completion probability of the full model is 0.9558, and the task failure probability is 0.48%, which can simultaneously preserve random arrival, recovery branch, failure state, and resource exclusivity constraints. After removing the random term of arrival rate, the completion probability rises to 0.9721, and the average completion time is shortened, which indicates that the arrival disturbance is one of the sources of uncertainty in the tail of the plan. After removing the random term of recovery rate, the completion probability is reduced to 0.9314, and the task failure probability is increased to 0.71%, which indicates that the recovery branch has an obvious correction effect on the failure trajectory. After removing the failure transfer, the completion probability rises to 0.9865, but the task failure probability is compressed to 0, the model cannot express the unrecoverable events, and the reliability result is high. After removing the exclusive constraint of shunting locomotive, the average completion time is reduced to 218.7 minutes, but the result does not conform to the sequential operation logic of single shunting locomotive in marshalling yard.

Based on the above, it can be seen that the arrival rate mainly affects the state transition rhythm of the main controller, the recovery rate mainly affects the speed at which the failed branch returns to the normal operation chain, and the shunting locomotive exclusive constraint determines the sequential dependence among the three trains. Perturbation experiments and ablation experiments together show that statistical model checking can put stochastic timing parameters, automata state transitions and plan completion probabilities into the same verification framework. The results of this section further show that the reliability evaluation cannot only rely on a single simulation curve, but should retain probability query, failure state, resource constraint and confidence interval at the same time, so as to accurately reflect the execution state of railway marshalling yard operation plan under uncertain conditions.

5 Conclusion

This paper focuses on the reliability evaluation of railway marshalling yard operation plan, and constructs a calculation method based on statistical model checking. In this paper, the main controller, train, shunting locomotive and hump signal system in hump disassembly process are abstracted as timed automata with stochastic time semantics, and the events such as disassembly start, hump authorization, batch roll-off, failure feedback and recovery confirmation are described by synchronous channels. This modeling method transforms the disassembly plan which depends on operation experience into a computer model which can be run, queried and counted, so that the completion probability of the plan, the expectation of the number of rail cars and the probability of unrecoverable failure can be verified in a unified state space.

Experimental results show that the number of cars in track 1 converges from 5 to 7 under the given hump configuration and three-train unpacking plan, indicating that the model can correctly reflect the relationship between batch roll-off and classified track count. The unrecoverable failure probability of the disassembly scheme is 0.48%±0.01%, which indicates that the original plan has a low failure risk under the joint effect of the HAC roll-off success rate and the recovery branch. The completion probability of train (0) stabilized above 0.99 after 150 minutes, train (1) entered the high completion probability interval after 240 minutes, and train (2) reached 0.9558 at 330 minutes. This result indicates that the single shunting locomotive, the number of batches and the preorder waiting time jointly determine the reliability boundary at the tail of the plan.

The perturbation experiments further show that the arrival rate mainly changes the occupation time of the intermediate state of the main controller, and the recovery rate mainly affects the speed of the failed branch to return to the normal job chain. Under the condition of high recovery rate, the completion probability of subsequent trains converged faster. With low recovery rates, latency is propagated backward along the sequential job chain. Ablation experiments also show that if the failure transfer or shunting locomotive exclusive constraints are removed, the model will overestimate the plan completion ability and weaken the expression of the real operation logic in the yarding yard.

There are still some limitations in this paper. The experimental scenario only contains a typical hump yard and three incoming trains, and the classification track size, number of shunting locomotives and fault types have not yet covered the more complex yard organization. The arrival rate, recovery rate and roll-off success rate in the model are set by parameterization, and more field operation data are still needed for calibration. The follow-up research can access real-time operation logs, HAC equipment status and compartment positioning data, establish an online dynamic parameter update mechanism, and extend multi-locomotive cooperation, classify track conflicts and dynamic reordering scenarios, so that the statistical model checking can move from off-line plan evaluation to real-time reliability judgment during operation.

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References

[1] Basile D, ter Beek M H, Ferrari A, et al. Exploring the ERTMS/ETCS full moving block specification: an experience with formal methods: D. Basile et al[J]. International Journal on Software Tools for Technology Transfer, 2022, 24(3): 351-370.

[2] James P, Moller F, Pantekis F. OnTrack: Reflecting on domain specific formal methods for railway designs[J]. Science of Computer Programming, 2024, 233: 103057.

[3] Ferrari A, Mazzanti F, Basile D, et al. Systematic evaluation and usability analysis of formal methods tools for railway signaling system design[J]. IEEE Transactions on Software Engineering, 2021, 48(11): 4675-4691.

[4] Haxthausen A E, Fantechi A. Compositional verification of railway interlocking systems[J]. Formal Aspects of Computing, 2023, 35(1): 1-46.

[5] Versluis N D, Quaglietta E, Goverde R M P, et al. Real-time railway traffic management under moving-block signalling: A literature review and research agenda[J]. Transportation research part C: emerging technologies, 2024, 158: 104438.

[6] D'amato L, Naldini F, Tibaldo V, et al. Towards self-organizing railway traffic management: concept and framework[J]. Journal of Rail Transport Planning & Management, 2024, 29: 100427.

[7] Sharma B, Pascariu B, Pellegrini P, et al. A real-time railway traffic management approach preserving passenger connections[J]. IEEE Access, 2024, 12: 79066-79081.

[8] de Weert Y R, Gkiotsalitis K, Van Berkum E C. Improving the scheduling of railway maintenance projects by minimizing passenger delays subject to event requests of railway operators[J]. Computers & Operations Research, 2024, 165: 106580.

[9] Leutwiler F, Filella G B, Corman F. Accelerating logic-based Benders decomposition for railway rescheduling by exploiting similarities in delays[J]. Computers & Operations Research, 2023, 150: 106075.

[10] Agasucci V, Grani G, Lamorgese L. Solving the train dispatching problem via deep reinforcement learning[J]. Journal of Rail Transport Planning & Management, 2023, 26:

100394.

[11] Sartor G, Mannino C, Nygreen T, et al. A MILP model for quasi-periodic strategic train timetabling[J]. Omega, 2023, 116: 102798.

[12] Polinder G J, Cacchiani V, Schmidt M, et al. An iterative heuristic for passenger-centric train timetabling with integrated adaption times[J]. Computers & Operations Research, 2022, 142: 105740.

[13] Reynolds E, Maher S J. A data-driven, variable-speed model for the train timetable rescheduling problem[J]. Computers & Operations Research, 2022, 142: 105719.

[14] Croella A L, Dal Sasso V, Lamorgese L, et al. Disruption management in railway systems by safe place assignment[J]. Transportation science, 2022, 56(4): 938-952.

[15] Kloster O, Luteberget B, Mannino C, et al. An optimization-based decision support tool for incremental train timetabling[C]//Operations Research Forum. Cham: Springer International Publishing, 2023, 4(3): 65.

[16] Bridgelall R, Tolliver D D. Railroad accident analysis by machine learning and natural language processing[J]. Journal of Rail Transport Planning & Management, 2024, 29: 100429.

[17] Mafokosi K R M, Pretorius J H C, Chattopadhyay G. Modeling of impact of operations and maintenance on safety, availability, capacity, and cost of Railways-A System dynamics approach[J]. Journal of Rail Transport Planning & Management, 2024, 31: 100463.

[18] Plissonneau A, Jourdan L, Trentesaux D, et al. Deep reinforcement learning with predictive auxiliary task for autonomous train collision avoidance[J]. Journal of Rail Transport Planning & Management, 2024, 31: 100453.

[19] Farrando R, Farhi N, Christoforou Z, et al. A mathematical model for a two-service skip-stop policy with demand-dependent dwell times[J]. Journal of Rail Transport Planning & Management, 2024, 31: 100461.

[20] Zien M, Kirschstein T. A rolling horizon approach for shunting operations–An emission oriented simulation study[J]. Cleaner Logistics and Supply Chain, 2023, 6: 100093.

[21] Leutwiler F, Corman F. A logic-based benders decomposition for microscopic railway timetable planning[J]. European Journal of Operational Research, 2022, 303(2): 525-540.