Design and Verification of Situation-aware Real-time Systems

by

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The above committee determined that the thesis is acceptable in form and content and that a satisfactory knowledge of the field covered by the thesis was demonstrated by the candidate during an oral examination. A signed copy of the Certificate of Approval is available from the School of Graduate and Postdoctoral Studies.

ABSTRACT

A real-time system (RTS) is usually well-defined and operates based on a specific model defined during system design. However, the RTS can interact with different objects from its environment and needs to satisfy a number of user-defined constraints such as safety (defined using the probability of failure) and performance (defined using the percentage of usage). Such requirements create the necessity for the RTS to be aware of its design and execute a set of additional tasks (apart from the tasks whose order is defined by a particular scheduler during system design) in response to the events which take place in the environment.

This thesis presents the design of a situation-aware RTS which can characterize the environmental situations through monitoring the system environment, analyzing the input obtained from the environment and identifying real-world occurrences as events. Additionally, we determine the real-time and non real-time properties associated with the events, identify the relationships involved among the events and create a knowledge-base offline which facilitates a reduced size of data for storage and processing.

We present a situation-aware task model (SATM) which efficiently maps the identified environmental events to a set of (predefined) adaptive tasks offline. This thesis also presents a validation framework which determines the user-defined safety, and performance constraints. We consider that the situation-aware RTS has two modes of operation: safety, and performance. The validation framework performs an online identification of the expected mode based on the user-defined constraints, checks whether the RTS is operating in the correct mode or not and allows the RTS to change its operating mode (if necessary).

To demonstrate the applicability of the proposed situation-aware RTS and usability of the SATM, the experimental analysis of the thesis is performed using three case studies: an automotive system, a real-time traffic monitoring system and an unmanned aerial vehicle (UAV) system which include RTS that are in motion and static. For the automotive system case-study, the experimental results of this thesis show that we identify 17234 events in 3241 environmental situations. The system operates in performance mode in 3295 situations and in safety mode in 126 situations when the probability of failure is high. The system consists of five tasks in the performance mode and three tasks in the safety mode and the corresponding constructed SATM contains nine vertices (adaptive tasks) and 68 edges. For each case-study, the constructed SATM provides an improvement in terms of scheduling overhead (up to 21%) and adaptation time (up to 49%) with respect to existing task models task models such as generalized multiframe model (GMF), non-cyclic generalized multiframe model (NC-GMF), recurring branching (RB), recurring real-time task (RRT), and non-cyclic recurring real-time task model (NC-RRT).

AUTHORS DECLARATION

I hereby declare that this thesis consists of original work of which I have authored. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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STATEMENT OF CONTRIBUTIONS

The contributions of the thesis are listed as follows:

Contribution 1: In Chapter 3, we present the design of a situation-aware real-time system which identifies real-time occurrences from the system environment as events, determines their properties, identifies the relationships among the events, characterizes the environmental situations in terms of events and creates a knowledge-base which allows faster information retrieval in a reduced memory space (in comparison to raw input data).

Contribution 2: In Chapter 4, we form a situation-aware graph-based task model by identifying the adaptive tasks needed to be executed in response to the current situations based on the detected events, evaluating the adaptive task defining a number of timing constraints and including the tasks in the proposed task model if the constraints are met.

Contribution 3: In Chapter 5, we present a validation framework that uses the knowledge-base to analyze the user-defined (safety and performance) constraints of the situation-aware real-time system, identifies the expected mode, determines whether the system is operating in the expected mode or not, and triggers a verification action (if necessary) which allows the system to switch the mode.

Parts of Contribution 1 and Contribution 3 presented in Chapter 3 and Chapter 5 have already been published as:

- Islam, Nayreet, and Akramul Azim. "A multi-mode real-time system verification model using efficient event-driven dataset." Journal of Ambient Intelligence and Humanized Computing, pages: 1-14, 2018.
- Islam, Nayreet, and Akramul Azim. "CARTS: Constraint-based analytics from real-time system monitoring." Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp: 2164-2169, 2017, Canada.
- Islam, Nayreet, and Akramul Azim. "Assuring the runtime behavior of self-adaptive cyber-physical systems using feature modeling." Proceedings of the 28th Annual International Conference on Computer Science and Software Engineering (CASCON), pp: 48-59, 2018, Canada.

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Abbreviations

RTS	Real-time system
OEM	Operational environment model
SATM	Situation-aware graph-based task model
UAV	Unmanned aerial vehicle
CNN	Convolutional Neural Network
RNN	Recurrent neural network
LSTM	Long short-term memory
GMF	Generalized Multiframe Model
NC - GMF	Non-cyclic Generalized Multiframe Model
RB	Recurring Branching Task Model
RRT	Recurring Real-time Task Model
NC - RRT	Non-cyclic Recurring Real-time Task Model
EDF	Earliest Deadline First
TINA	Time Petri Net Analysis
YOLO	You Only Look Once
SIL	Safety Integrity Level
TC	Timing Constraints
GC	Graph-based Constraints

Chapter 1

Introduction

Real-time systems are those computing systems which need to react within a precise time in response to an event taking place inside the system or in the environment [1]. Such systems often include a number of concurrent tasks sharing the execution processors [2]. A task can be defined as the real-time computation that is executed by the processor in a sequential fashion [1]. Real-time computations are extensively integrated (in part or completely) to a number of application domains such as Automotive, Avionics, Railway, Telecommunication, Robotics and Military [1].

Correct behavior of an RTS depends not only on the value of the computation associated with the task but also the time at which the task has finished its execution. For example: upon the detection of a collision, an automotive real-time system needs to execute the task which activates the airbag. Late activation of the airbag may result in driver hitting the steering wheel. Hence a missed deadline of any real-time task can result in catastrophic consequence or may lead to significant loss. Therefore, the RTS must be designed carefully so that the system can guarantee meeting the deadlines of the tasks.

1.1 Design aspects of real-time systems

Several design aspects exist that must be carefully defined and reviewed by the RTS designers which include timeliness, schedulability, and multi-mode operation. These aspects make the design of an RTS challenging. The real-time system can achieve predictability by satisfying the design aspects described as follows:

1.1.1 Timeliness

Tasks with strict timing constraints characterize an RTS. The timing constraints associated with the tasks need to be satisfied in order to accomplish the expected behavior [1]. One of the common timing constraints of the real-time task is its deadline. The deadline of a task represents the time before which it must complete its execution [1].

For example, an automotive RTS can contain a task for fuel injection whose relative deadline is 40 milliseconds which means it must complete its execution within next 40 milliseconds with respect to the arrival time of the task. The designer of the RTS specifies the tasks to be handled by the system and the general timing requirements associated with the tasks that the system must satisfy.

1.1.2 Schedulability

An RTS may need to execute several tasks which can overlap in time. The processor of the RTS needs to be assigned to the various tasks based on a certain predefined criterion called a scheduling policy. The RTS can interrupt the running task so that important tasks can gain the processor immediately upon arrival. The operation of suspending a running task is called preemption. A scheduling algorithm can be defined as a set of rules that, at any time, determines the order in which tasks are executed [1]. A schedule of a set of tasks is said to be feasible if all the tasks can complete their execution according to a set of predefined constraints [1]. A set of tasks is said to be schedulable if there exists at least one algorithm that can produce a feasible schedule. The RTS must be able to determine the schedulability.

A number of techniques have been proposed in the literature for scheduling the real-time tasks. If the task executions can be interrupted, the scheduling policy is called preemptive scheduling [3]. Otherwise, the policy is called non-preemptive scheduling [4]. Static cyclic scheduling implies the off-line generation of a fixed schedule table that will be followed at runtime to order task executions [5, 6]. Priority based scheduling policies select and execute the task with the highest priority when there are requests from multiple tasks. Depending on whether the priority of a task is constant or not, priority-based scheduling can be further divided into two groups, static priority scheduling and dynamic priority scheduling [1, 7].

1.1.3 Multi-mode operation

An RTS today is often expected to operate in multiple modes. Each operating mode corresponds to specific behavior and characterized by a set of tasks. For example, an RTS can have a low power mode which aims to decrease the power consumption by reducing the number of running tasks. The RTS initiates a mode change if it detects any change in its environment or within the system. To change the operating mode, from current to old, it is necessary to remove some old mode tasks and add some new mode tasks which introduce a temporary overload. The design must guarantee that no deadlines will be missed during mode transition. Over the past years, several mode-change protocols have been studied [8, 9]. The primary goal of the existing mode change protocols is to ensure that the system does not violate any deadlines during a mode change.
The RTS designers review the timing, schedulability, and multi-mode design aspects of the system during the design phase. If all the aspects are satisfied, the design will proceed with the final synthesis of the low-level hardware/software implementations.

1.2 Challenges with the state-of-the-art in real-time systems

Designing and predicting the runtime behavior of the RTS is challenging. The majority of these challenges come from the fact that the system can interact with various objects from the environment at runtime. Such interactions are often characterized by strict safety constraints of which violation might lead to catastrophic consequences. Even a non-critical system can turn into safety or mission-critical due to these interactions [10]. For example, the majority of the failures of vehicles running on the road take place due to the vehicular system interactions with other objects such as pedestrians and vehicles [11]. Many industrial application domains (e.g., avionics, and automotive) use RTS and have a high demand for dependability. Such systems need to facilitate flexibility and reliability by changing its operating mode at runtime with respect to any changes in the environment [12].
Existing works on RTS design and verification aim to ensure the functional behavior by performing activities which include design analysis, safety analysis, and testing [13] without taking the operational environment into consideration. However, even a well-designed RTS can interact with different objects from its environment at runtime and

experience safety issue (for instance the probability of failure) and performance issue (e.g., increased response time). The environment of an RTS is uncertain. The design of the RTS needs to provide assurance such that the system can guarantee the defined functionality or handle failure cases by triggering appropriate reactions in different uncertain situations. Such assurance requirements create the necessity for designing a situation-aware RTS which ensures a runtime behavior which is adaptive.

1.3 Thesis objectives

The RTS can interact with multiple objects from its environment at runtime. The system needs to assure functional and timing behavior because of the safety-critical nature of the interactions by executing a set of adaptive tasks in response to the environmental events. The RTS also needs to satisfy the user-defined constraints which can be translated to operation in the expected mode.

We present a validation framework which determines the expected mode at runtime based on the user-defined constraints (which in our work are safety and performance), checks whether the RTS is operating in the expected mode or not. During the determination of the expected mode, the framework provides preference on safety over performance constraint and thereby ensures that the RTS does not fail even in the presence of adverse environmental situations. The RTS can guarantee meeting the constraints by switching from current to expected mode (if necessary) at runtime. Hence, the proposed design of the situation-aware RTS tackles the following challenges,

- Allows the RTS to characterize the environmental situations in terms of events.
- Facilitates adaptability by executing a set of adaptive tasks which allow the RTS to handle a particular environmental situation without violating any timing constraints.
- Satisfies the user-defined constraints by identifying the expected operating mode and allowing the system to switch to the expected mode at runtime.

1.4 Design and verification of situation-aware real-time systems

We present the design of situation-aware real-time systems which contain two types of execution model which are non-adaptive and adaptive execution models. In non-adaptive execution model, the situation-aware RTS executes only those tasks which are characterized by current mode using the Earliest deadline first (EDF) scheduling algorithm. In other words, the non-adaptive execution model does not take the system interactions with the environment into consideration.

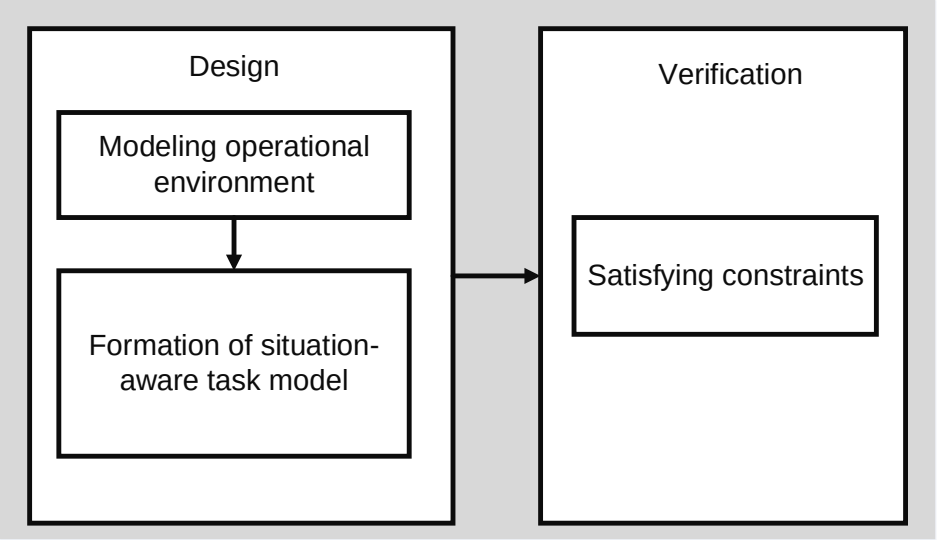


FIGURE 1.1: Design and verification of the situation-aware real-time system

In the adaptive execution model, the situation-aware RTS uses an operational environment model as presented in Figure 1.1 to characterize the environmental situations in terms of detected events. We also form a situation-aware task model as shown in Figure 1.1 which allows the proposed system to execute adaptive tasks in response to the environmental events.

Due to the presence of safety constraints, a system requires a pessimistic upper bound on execution times of tasks which can be translated to over-provisioning of resources when the probability of failure is less. For example, the design of a real-time communication application can consider worst-case message transmission time between the sender and the receiver. Such design involves over allocation of various communication resources. This over-provisioning of resources may reduce the usage or throughput of the system,

which we define as the performance constraint. In this thesis, we assume that a situation-aware real-time system operates into two different modes depending on either safety or performance requirements. While the safety mode focuses on guaranteeing reliability such that the system exhibits less probability of failure, performance mode is focused on the increased percentage of usage. The verification of the proposed situation-aware RTS includes satisfying safety and performance constraints at runtime by operating in the expected mode as illustrated in Figure 1.1.

To identify the expected mode, it is required to monitor the environment of the situation-aware RTS, identify different real-world occurrences as events and determine their real-time and non real-time properties. For example, the real-time properties associated with an event can be duration and period whereas the non real-time properties are location and speed. A knowledge-base of the situation-aware RTS can allow us to analyze the characteristics of system behavior along with its users and the environment. Therefore, in this thesis, we present an operational environmental model which creates a knowledge-base offline from processing the monitored environmental input stream. The knowledge-base allows faster information retrieval in a reduced memory space (in comparison to raw environmental input) which is suitable for the situation-aware RTS.

1.5 Contributions

The contributions of this thesis can be viewed as identifying real-time occurrences as events along with their timing properties from monitoring the environmental input streams of the RTS. Moreover, we provide an efficient way to form a knowledge-base from the monitored environmental input streams which consumes significantly less memory and allows faster processing. We also perform a deductive failure analysis which takes components and events present in the environmental situation and deducts the probability of failure. We determine system performance (current usage) in each environmental situation. The results of such identifications allow the validation framework to satisfy the user-defined constraints such as safety and performance in response to different environmental situations by changing the RTS mode of operation at runtime.

For each environmental situation, we identify the adaptive tasks that are needed to be activated. We evaluate the adaptive tasks using a set of predefined timing constraints and avoid including the tasks which violate the constraints. The contributions of the thesis are listed as follows:

1. Designing a situation-aware RTS which,

   (a) Identifies real-time occurrences as events, determines their real-time and non real-time properties, identifies the relationships involved among the events and characterizes the environmental situations in terms of events.

   (b) Creates a knowledge-base which allows faster information retrieval in a reduced memory space (in comparison to raw input data).

2. We form a situation-aware task model which,

   (a) Identifies the adaptive tasks needed to be executed in response to the current situations based on the identified events. Each task can be added to the proposed task model as a vertex and the execution order between a pair of tasks as an edge. While including the adaptive tasks, we ensure timing requirements by defining a number of constraints and include the vertices in the proposed task model if the constraints are met.

   (b) Moreover, we use existing task models such as GMF [14], NC-GMF [15], RB [16], RRT [17], and NC-RRT [18], to execute the adaptive tasks obtained from different situations (these task model were chosen because they allow characterization of the tasks which have non-deterministic activation pattern).

3. We present a validation framework that satisfies the user-defined constraints by,

   (a) Using the real-time and non real-time properties of the detected events to analyze the safety and performance constraints of the RTS.

   - Identification of the safety constraint involves performing a fault-tree analysis and determining the probability of failure of the RTS in each environmental situation.
   - Identification of the performance constraint of the RTS involves determining its usage (throughput).

   (b) Characterizing its runtime behavior of the RTS in terms of modes.

   (c) Using the safety constraint of the system to identify the expected mode and determining whether the RTS is operating in the expected mode or not.

   (d) Triggering a verification action (if necessary) which allows the RTS to switch the mode.

1.6 Novelty of the thesis

The novelty of this research can be viewed as designing a situation-aware real-time system which satisfies the user-defined constraints through switching to the expected mode and executing adaptive tasks using a situation-aware task model. Therefore, the proposed situation-aware RTS can collect information on the system behavior at runtime through monitoring and allows characterization of behavior regarding each experienced situation stored in the knowledge-base.

The validation framework uses real-time and non real-time properties of the detected events to identify the safety constraint of the RTS. The framework also allows the RTS to characterize its runtime behavior. While determining the expected mode, validation framework does not compromise safety over performance constraint. For example, situations in which both the probability failure and usage requirements are high, the model identifies safety as the expected mode, and the RTS ensures reliability by switching the mode (if the system is operating in performance mode).

Moreover, we present a SATM which ensures adaptive behavior in different situations by executing adaptive tasks in response to the events at runtime. If added, the SATM can adapt to a particular situation when the next time it appears again. Therefore, in the worst-case, we allow no adaptation for a given situation if it is unfeasible or yet unprocessed to be added to the SATM. This thesis can benefit several application domains such as automotive, traffic, agriculture, avionics, and railway systems because the situation-aware RTS can verify the runtime behavior and adapt to the current environmental situation.

1.7 Organization of the thesis

The thesis is arranged in seven chapters. In Chapter 2, we discuss the preliminaries related to the situation-aware real-time system which helps the reader to understand and follow the remainder of the thesis. Chapter 2 also highlights the related works on various design and validation aspects of the situation-aware RTS and provides an overview of how our contributions differ from the existing works. In Chapter 3, we demonstrate the components which are considered in designing a situation-aware RTS such that it can characterize different environmental situations. In Chapter 4, we discuss the workflow of the situation-aware real-time system where we present various phases of capturing

situations from the environment, the formation of the knowledge-base, and the adaptive and non-adaptive execution model of the system. Chapter 4 also focuses on identifying adaptive tasks from the environmental situations which can be executed using a number of existing task models. Moreover, we present a novel situation-aware graph based task model in Chapter 4. We discuss its characteristics, steps, and methodologies involved in the formation of the proposed task model. In Chapter 5, we discuss the validation of the situation-aware RTS with respect to safety and performance constraints which include the identification of the expected mode at the runtime and checking whether the real-time system is operating in the correct mode or not. Chapter 5 also discusses our approach to ensure reliability by allowing the RTS to switch the mode (if necessary). In Chapter 6, we present the experimental analysis of the thesis using three case studies. Chapter 7 concludes the thesis and points out possible future research directions in the context of situation-aware real-time system design analysis.

Chapter 2

Literature review

2.1 Introduction

With the increasing use of RTS in different application domains, it is essential for the designers to guarantee meeting the user-defined constraints at runtime. Traditional assurance techniques consist of different methods which include verification, validation, and certification that can be used to guarantee that the system meets certain predefined constraints. However, these techniques do not take system interactions with various components of the operational environment into consideration. Uncertainties in the execution environment of the RTS impose challenges on predicting as well as assuring the runtime behavior during system design.

The design techniques which address the assurance of the user-defined constraints at runtime has, thus, become a high priority in the RTS research community. The requirements to assure the user-defined constraints in uncertain environmental situations has motivated us to investigate innovative approaches for designing a situation-aware RTS. This chapter presents an overview of the fundamental terminologies and components of the situation-aware RTS in Section 2.2. Section 2.3 presents a discussion on the related works in this area and compares them with the methodologies used in this thesis.

2.2 Fundamentals

2.2.1 Real-time system task model

We define the task as a unit of execution (computation that is sequentially executed by the processor) in the RTS. A task that can potentially be executed on the processor is

defined as an active task. Active tasks that are ready to be executed on the processor are stored in a waiting task queue. Each active task τ_i, in our system can be defined as $\tau_i = (\alpha_i, C_i, D_i)$, where α_i is the arrival time, C_i is the worst-case execution time demand, D_i is the relative deadline of τ_i such that $i \in \mathbb{N}^+$.

Example 2.1. ***Task:*** *Consider an automotive RTS which contains a task for fuel injection whose timing parameters (in milliseconds) can be defined as (10,20,40), where 10 ms is the arrival time of the task, 20 ms is the worst-case execution demand, and 40 ms is the relative deadline of the task.*

2.2.1.1 Internal task set

Internal real-time task set contains those active tasks which periodically take place within the RTS based on a particular scheduling algorithm defined during system design. The RTS considered in this work consists of two modes $\mu = \{\mu_1, \mu_2\}$, where μ_1 represents safety mode and μ_2 represents performance mode. Each mode contains its own set of tasks.

In this thesis, the safety mode contains a set of m active internal real-time tasks $\tau_{in}^{\mu_1} = \{\tau_1^{\mu_1}, \tau_2^{\mu_1}, \ldots, \tau_m^{\mu_1}\}$ and the performance mode contains a set of q active internal real-time tasks $\tau_{in}^{\mu_2} = \{\tau_1^{\mu_2}, \tau_2^{\mu_2}, \ldots, \tau_q^{\mu_1}\}$ as illustrated in Figure 4.2 where $m, q \in \mathbb{N}^+$. We consider each internal task $\tau_i \in (\tau_{in}^{\mu_1} \cup \tau_{in}^{\mu_2})$ as periodic which appears at a regular interval with a period P_i, where $P_i > 0$. A task τ_i can have different iterations due to its activation at different times. Therefore, we can view task τ_{ij}, as the jth iteration of τ_i such that $j \in \mathbb{N}^+$.

Example 2.2. ***Internal task set:*** *Each mode of an automotive RTS can contain a different set of tasks. Table 2.1 presents an example of the internal task set for both safety and performance mode along with their timing parameters. Here, the fourth timing parameter is the period of the task.*

TABLE 2.1: An example list of internal task set in Safety and Performance mode.

Task name	Timing parameters in Safety mode	Timing parameters in Performance mode
Speed measurement	(10,10,100,100)	(10,10,100,100)
Fuel injection	(10,20,80,80)	(10,15,80,80)
ABS control	(10,40,80,80)	(10,30,90,90)
Temperature measurement		(10,10,100,100)
GPS data acquisition		(10,10,100,100)

Definition 2.1. Demand-bound function: For any time interval δ and a set of tasks τ_{in}, demand-bound function $\text{dbf}_{\tau_{\text{in}}}(\delta)$ (according to [19]) is the maximum cumulative worst-case execution time for all $\tau_{\text{i}} \in \tau_{\text{in}}$ which have both deadlines and arrival times within δ.

2.2.1.2 Adaptive task set

Adaptive real-time task set contains those active tasks which arrive in the waiting queue due to the events that take place in the environment of the RTS. Our system also consists of a set of r adaptive real-time tasks τ_{out} which can be activated at runtime. An adaptive real-time task $\tau_{\text{out}_{\text{i}}} \in \tau_{\text{out}}$ in our system is aperiodic.

Example 2.3. ***Adaptive task:*** *Assume that, upon the detection of a traffic signal which has turned red, a situation-aware automotive RTS can stop through activating the task for braking (adaptive task) with timing parameters (10,30,60).*

Definition 2.2. Request function: For any time interval δ and a set of tasks τ_{out}, request function $\text{rf}_{\tau_{\text{out}}}(\delta)$ is the accumulated worst-case execution demand of each task $\tau_{\text{out}_{\text{i}}} \in \tau_{\text{out}}$ that can be released in δ.

For the RTS, building a realistic model which provides complete knowledge of the system and its environment is challenging [20]. The system can interact with numerous real-world entities from the environment continuously. We can use the data stream received from the environment to characterize the environmental situations along with its users. One of the main challenges in characterizing environmental situation is the identification of objects.

Definition 2.3. Object: An object O_{b}, in this thesis, can be defined as any component capable of movement or undergoing any change in its state or behavior such that $\text{b} \in \mathbb{N}^{+}$.

Example 2.4. ***Object:*** *Environmental entities such as cars and people in a situation-aware automotive RTS can be considered as objects.*

The RTS can also encounter different real-world occurrences which we define as events.

Definition 2.4. Event: An event E_{c}, in this thesis, is specified as a real-world occurrence that can be expressed over time and space, such that $\text{c} \in \mathbb{N}^{+}$. Each event E_{c} occurs in a particular location, has a duration, and is associated with particular changes in its state.

Example 2.5. ***Event:*** *The movement of a pedestrian from one side of the road to another in the environment of a situation-aware automotive RTS can be considered as an event.*

Apart from the detection of events associated with different objects, we perform identification of those events that are the result of interaction between two or more events by defining a rule set called AR. We classify the events as basic E_{basic} and derived events $E_{derived}$. Derived events take place due to the interactions among existing events. Each row in AR defines a set of events that are in association with each other using a rule, which can be given as, $E_{basic} \Rightarrow E_{derived}$.
From each row of AR, we learn some rules in terms of events. From all possible rules, we identify the rules which are valid and select them while determining the derived events by calculating support (refers to the frequency of the event) and conviction values (the ratio of the frequency where E_{basic} takes place without $E_{derived}$).

Definition 2.5. Situation: At a particular time t_k, we view an environmental situation $S_k = \{E_1, E_2, \ldots, E_d\}$, as the collection of interactions among various events present in the environment of the system with $k, d \in \mathbb{N}^+$.

The considered RTS can form a knowledge-base based on the properties of events in each situation which allows faster analytics and storage ability. To form the knowledge-base, we perform an analysis of various behavioral patterns of the system and extract different real-time and non real-time properties. We also classify the events into periodic, and aperiodic based on their timing properties. The knowledge-base captures different situations $S = \{S_1, S_2, \ldots, S_n\}$ in terms of events and interactions among various events and objects at each timestamp. For each situation, we also determine the safety and performances constraints associated with all the components and events identified from the environment of the system.

2.3 Related works

2.3.1 Real-time task model

Real-time task models have been extensively studied in the context of scheduling [1]. Many task models have been proposed which allow analysis and specification of real-time tasks. The research community of RTS has presented a number of tasks models [3, 7, 21] which allow characterization and analysis of real-time tasks. Baruah et al. presents

GMF [19] which generalizes the multiframe model by defining a GMF task using vectors of minimum inter-release separations, worst-case execution times and relative deadlines. Moyo et al. propose the Non-Cyclic GMF model [15] which is syntactically identical to the GMF task model but with non-cyclic semantics. Baruah et al. proposed RB [19] based on the observation that real-time code may contain branches which influence the pattern in which tasks are released. An RB model can be characterized using a tree which represents task releases along with their minimum inter-release separation times. This model was extended to the RRT task model [17] which has an additional period parameter which represents the minimal time between two releases of tasks (represented by the source vertex). The model was further extended to NC-RRT task model [18] which does not contain one single sink vertex as opposed to RRT. Researchers from multiple communities have also explored models which deal with numerous aspects of adaptation which include requirements analysis, design, and specifications as well as lifecycle phases like development time, design time, configuration time, and runtime.
We determine the adaptation requirements at runtime and present a SATM which executes various adaptive tasks (along with internal tasks) based on the current situation. While the existing work focuses on assuring functional and non-functional requirements through adaptation, we look into the adaptation process itself and guarantee timing behavior during adaptation by evaluating the adaptive tasks with respect to some predefined timing and graph-based constraints. Our contribution differs from the existing works as we form a knowledge-base by performing extraction of the properties from the detected events. The RTS characterizes situations in terms of events and identifies adaptive tasks. We use the execution model to evaluate the newly identified adaptive tasks and use the SATM to guarantee the functional as well as timing requirements at runtime.

2.3.2 Situation characterization

Works presented in [22] and [23] demonstrate approaches that can detect various events from video streams. Some works on video data mining can also be found which use techniques like semantic indexing presented by [24] and fixed-location monitors from [25]. Various techniques like H.261 [26]), MPEG-1 [27]), MPEG-2 [28] are also present which performs compression of video data.

Some of the techniques discussed above perform compression of the video data, (sometimes even up to 50 percent). However, since the resultant output is non-structured, complexity still exists in video information retrieval. In this case, we need to process an enormous amount of data presented in pixel format which makes the operations computationally expensive. Our contribution differs from these existing works as we form a knowledge-base by performing extraction of real-time and non real-time properties from the detected events. The knowledge-base presents system information in terms of events and consumes a significantly reduced memory in comparison to existing video data compression approaches.

2.3.3 Validation of real-time systems

Many methods have been proposed which aim to validate the behavior of a system. Generally, timers are introduced into validation by assigning upper and lower time bounds to transitions such as timed automata [29], Time Petri nets [30]. Various tools like Time Petri Net Analyzer (TINA) [31], Uppaal [32] validates whether the system meets specific real-time requirements or not. Many existing approaches can also be found for collision detection. A rule-based approach defining a set of rules to detect collisions is found in [33]. However, this method is unable to address dynamic and uncertain conditions. Use of physical model for detection of the crash is present in [34].

2.3.3.1 Safety analysis

We can also find some existing work in the real-time safety analysis. We notice a random probability distribution approach for risk assessment in [35]. Dynamic risk evaluation on sensor network observation is found in [36]. An analysis of information flow among computers, traffic signs and travelers is presented in [37].

We use the properties along with association rule mining to determine derived events that are the result of basic events. Our system uses timing properties to characterize events. We provide a safety analysis of the system using Bayesian techniques and fault-tree. We also deliver a performance analysis of the system providing capacity usage of the system in terms of event detection and processing.

Our work on using the validation framework to satisfy the user-defined constraints also differs from the existing approaches because we analyze the constraints such as performance and safety obtained from the knowledge-base and use the analytics to determine

the expected mode of the RTS. The validation framework compares the expected and current mode of the RTS and allows the RTS to switch its operating mode at runtime.

2.3.4 Self-adaptation

These approaches are a bit complex as we need to have a precise understanding of the application domain. The goal-oriented methods can effectively use functional requirements specification to derive assurance criteria [38]. During the development time, stakeholder expectations can be specified using goal model. Such models can be used to obtain the decision criteria for the system behavior which is acceptable at runtime. In addition, goals are a good candidate as assurance criteria in a system which has dynamic environments [39–41]. These goals can be decomposed into sub-goals to represent functional behavior at runtime. The system can select the most suitable decomposition path which ensures the expected runtime behavior.

A graph-transformation based approach was presented by Becker and Giese to model self-adaptive software systems [42]. This method checks the correctness of the self-adaptive system model through invariant-checking and simulation techniques. To verify a given set of graph transformation never reaches an unstable state, invariant checking methods are used which imposes linear complexity on the properties to be checked and the number of rules. Another approach exists which uses graph grammars semantics to specify models, their transformations and relations [43] which can be used as a basis for property analysis. Bucchiarone et al. have proposed an approach which formalizes dynamic software architecture as hyper-type grammer [44] which enables the completeness and the verification of correctness of self-repairing systems.

Our work takes the uncertainties which can be obtained from the environment of the RTS into consideration. We perform operational environment modeling to identify the expected operating mode in each environmental situation and satisfy the user-defined constraints by presenting a validation framework which allows the RTS to execute correct actions.

Our work also addresses the systems which execute multiple behaviors. As opposed to the works presented in Subsection 2.3.4 which can cover only a particular behavior, we present an RTS that can operate in two different modes depending on either safety or performance requirements. Here, the safety mode focuses on guaranteeing reliability while performance mode is focused on the increased usage (in terms of load). For each

adaptive tasks, we check if the tasks are violating any timing constraints or not. If all the tasks satisfy the timing constraints, we can include the task in an existing task model as well as the proposed SATM.

Chapter 3

Components of the proposed situation-aware real-time system

3.1 Introduction

An operational environment model is useful for characterizing and validating the functional and timing requirements of the RTS. Formation of the operational environment model requires monitoring the environmental situations of the RTS and gather information about the system environment which is essential towards building a model that has sufficient knowledge of all the possible interactions. The RTS can use inputs collected from the monitored environment to identify data patterns [45] which can help in characterizing the situations including the uncertainties of the system environment.

3.2 Operational environment model

The operational environment model considered in this thesis consists of mainly three components which include a data capture module, a detection module and an analytics module as shown in Figure 3.1. The operational environment model uses the data capture module to monitor the environment of the RTS. The operational environment model also performs real-time detection and classification of objects, tracks the objects in subsequent time intervals, as well as identifies events using a detection module. The analytics module of the operational environment model extracts the real-time, and non real-time properties of the detected events, classifies the events in terms of their periodicity and characterizes the environmental situations.

Example 3.1. *Consider a situation-aware automotive RTS which monitors its environment at runtime. The system interacts with the objects of its environment and needs to satisfy the user-defined constraints such as safety (probability of failure) and performance (percentage of usage) at runtime. Assume that the probability of failure = .25 is the designer-defined threshold, such that if the probability of failure is higher than .25, the automotive RTS is expected to operate in safety mode. At a particular situation the automotive RTS can,*

- *identify an* ***object*** *such as a* ***traffic signal****.*
- *detect an* ***event*** *such as* ***change of the traffic signal from green to red****.*
- *identify* ***probability of failure = .35*** *and* ***percentage of usage = 56%****, therefore, determines* ***safety*** *as the* ***expected mode****.*
- *identifies* ***Speed measurement (10,10,100,100)****,* ***Fuel injection (10,20,80,80)*** *and* ***ABS control (10,40,80,80)*** *as the internal tasks characterized by safety mode.*
- *identifies* ***breaking (10,20,80)*** *as the* ***adaptive task*** *needed to be activated in response to the event* ***change of the traffic signal from green to red****.*

3.2.1 Data capture module

The data capture module contains sensors (such as Camera, Lidar, and Radar) which continuously provides the raw input stream of the environment of the RTS. The detection module takes the environmental input stream as the input $\mathrm{I} = \{\mathrm{I}_1, \mathrm{I}_2, \ldots, \mathrm{I}_\mathrm{n}\}$ at timestamps $\mathrm{T} = \{\mathrm{t}_1, \mathrm{t}_2, \ldots, \mathrm{t}_\mathrm{n}\}$ respectively where the arrival of each environmental input has a time interval $\delta = \mathrm{t}_\mathrm{k} - \mathrm{t}_{\mathrm{k}-1}$ such that $\mathrm{n}, \mathrm{k}, \delta \in \mathbb{N}^+$ and $1 \leq \mathrm{l} \leq \mathrm{n}$.

3.2.2 Detection module

The detection module is responsible for the identification of events from an environmental input. For each input, the detection module identifies the objects, classifies the objects, tracks the objects in subsequent time intervals and identifies the real-world occurrences associated with objects as events.

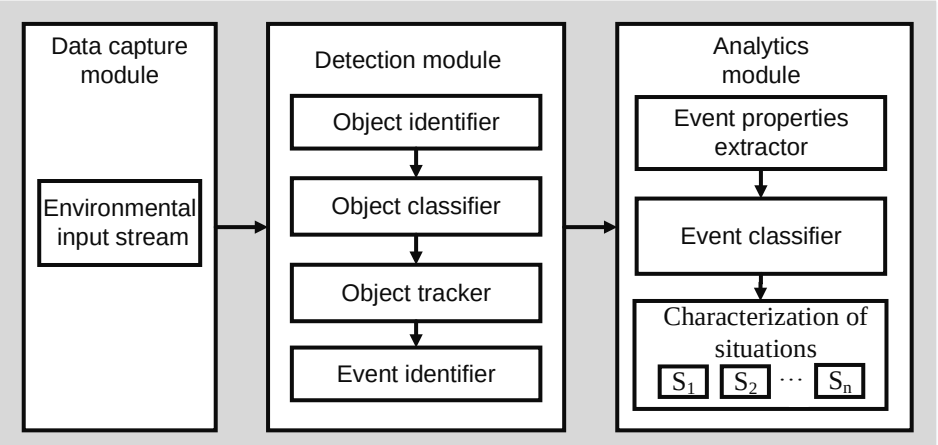


FIGURE 3.1: Components of operational environment model of the situation-aware real-time system.

3.2.2.1 Object identifier

We use the inputs obtained from the sensors (such as Lidar, Radar and Camera) to detect an object and identify different properties associated with the object from the RTS environment. We use the Lidar sensor to determine the location of an object and measure the distance of the object from the RTS. To measure the distance, we illuminate the object with pulsed laser light and use the Lidar sensor to measure the reflected pulses. The wavelengths and the laser return time differences are used to identify the type of the object. Hence, we use Lidar to determine the object type, location, and distance of the object from the RTS.

We use RADAR to detect objects within a specified range, and identify the location, object type along with the distance of the object from the RTS. The RTS considered in this work, also uses a camera to identify objects from its environment. We use the video data obtained from the camera as an input. To identify an object, we use the convolutional neural network which consists of two types of layers such as Convolutional, and Fully-Connected. In this work, for identifying an object, we use nine convolutional layers followed by two connected layers. Although the detection and classification occur at runtime, training the neural network is performed offline using the ImageNet dataset. We identify the object type, location, and the distance of the object from the RTS.

Sensor fusion is the approach for combining the data obtained from different sensors so that the resulting information is more accurate in comparison to the data which are individually obtained from the sensors. Each sensor provides three properties of an object such as object type, location, and the distance of the object from the RTS

which is combined using sensor fusion as presented in Figure 3.1. For each property, we combine the sensor inputs using the Central Limit Theorem. We apply sensor fusion to determine all the properties associated with an object and thereby detect an object.

3.2.2.2 Object classifier

For each detected object O_b, the object classifier presented in Figure 3.1 is responsible predicting the conditional class probability. For each environmental input, we classify the objects using CNN (which has been train on ImageNet dataset) at runtime. For each object O_b, we record the information which includes unique identification number of the object, the recorded time, location, state (like moving or static object in Example 3.1) and the speed of the object.

The RTS can interact with the objects at runtime and may need to execute additional operations due to these interactions. The operational environment model also detects events associated with the objects by tracking the objects as shown in Figure 3.1.

3.2.2.3 Object tracker

The next step of the detection module is to track and match the objects in the current environmental input with the objects identified in the previous environmental input. Algorithm 1 presents the steps and methodologies involved in tracking and matching objects for each newly arrived environmental input. When I_{n+1} becomes the current environmental input, the object tracker identifies the locations of all the objects. For each object O_b in I_n, object tracker defines a variable called FDL (in Line 5 of Algorithm 1) which denotes the maximum possible distance between two objects. The object tracker compares O_b with all the objects in I_{n+1} (in line 6 of Algorithm 1). Line 7 of Algorithm 1 defines function called distance$(O_b, O_{b'})$ which calculates the distance between two objects, O_b in I_n and $O_{b'}$ in I_{n+1}. The object tracker calculates minimum distance called LD by comparing O_b in I_n with all the objects in I_{n+1}. If the minimum distance is less than some pre-defined threshold TH, object tracker considers them as the same object by matching their id (as presented in line 13 and 14 of Algorithm 1). On the other hand, for the detected object $O_{b'}$ in I_{n+1}, if $O_{b'}$.least_distance is greater than threshold TH, the object tracker identifies it as a new object detected in I_{n+1} (as shown in line 16 of Algorithm 1).

Algorithm 1 Tracking and matching objects

```
1: procedure TRACK-AND-MATCH-OBJECTS(I_n, I_{n+1})
2:     OI_n ← {O_1^n, ..., O_q^n}, ∀(1 ≤ i ≤ q) : O_b ∈ I_n
3:     OI_{n+1} ← {O_1^{n+1}, ..., O_r^{n+1}}, ∀(1 ≤ j ≤ r) : O_{b'} ∈ I_{n+1}
4:     for all object O_b ∈ OI_n do
5:         O_b.least_distance ← FDL
6:         for each object O_{b'} ∈ OI_{n+1} do
7:             LD ← distance(O_b, O_{b'})
8:             if LD ≤ O_b.least_distance then
9:                 O_b.least_distance ← LD
10:                Index ← O_{b'}.id
11:            end if
12:        end for
13:        if O_b.least_distance ≤ TH then
14:            O_b.id ← Index
15:        else
16:            OI_{n+1} ← OI_{n+1} ∪ O_b
17:        end if
18:    end for
19: end procedure
```

Similarly, to determine any changes or modifications of the object behavior in the current environmental input, for each arriving environmental input, object tracker compares each object $O_{b'}$ in I_{n+1} with its previous condition in I_n. The object tracker considers that $O_{b'}$ did not undergo any significant modification or change when the difference is less than a threshold value (predefined) TH. However, if the difference is more than the predefined threshold, object tracker detects the change for the particular object. Therefore, object tracker can determine any changes in the behavior of the object. For example, in the automotive system presented in Example 3.1, changes in the location of the vehicle or pedestrian can be determined, or any variations in the color of the traffic light can be identified.

3.2.2.4 Event identifier

The event identifier defines an event E_c as the actions, changes or interactions with one or more objects. One of the essential tasks in the characterization of an environmental situation is the detection of events. In this thesis, the detection of events involves using Algorithm 1 to track various objects and identification of changes in their properties. With the arrival of new environmental input, any changes associated with an object is identified as an event.

Events that are associated with objects can be detected by the operational environment model from the environmental input stream through tracking. The event identifier uses a temporal data called ED and stores the information of the events related to the objects which can be defined as,

$$\mathrm{ED} = (\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{u}) \tag{3.1}$$

Where u is a natural number such that $\mathrm{u} \in \mathbb{N}^+$. For each event $\mathrm{E_c}$, in this thesis, the event identifier stores properties which include location, state, and speed in ED at different timestamp. Therefore, ED contains information regarding the events associated with each object and keeps track of the changes in its position and state recorded at different times.

3.2.3 Analytics module

An RTS can experience failure if the timing constraints are not adequately met. Therefore, exact calculations of timing constraints associated with the events are essential. It is also necessary to detect real-time and non real-time properties associated with an event. The analytics module is responsible for performing different steps which are the extraction of the properties of an event, classification of events based on their real-time properties and characterization of the environmental situations in terms of events as illustrated in Figure 3.1.

3.2.3.1 Event properties extractor

The analytics module extracts both real-time and non real-time properties associated with an event from the environmental input stream. For each event, the analytics module identifies its properties which include location, state, and speed using ED in different timestamps. The analytics module also uses ED to calculate the duration of each event which is the difference between the start time of an event with its completion time (or the time when it has moved out of the environmental input stream). For each event $\mathrm{E_c}$, we identify the start time of an event and its duration using ED defined in Equation 3.1. Duration $\mathrm{E_c}$.duration for any event $\mathrm{E_c}$ can be represented as:

$$\mathrm{E_c.duration} = \mathrm{E_c.endtime} - \mathrm{E_c.starttime} \tag{3.2}$$

Where, E_c.starttime and E_c.endtime are respectively the timestamp of start and end time of E_c. We use ED for identifying the periodicity of the events. We analyze ED at runtime and keep track of appearance of the events in different timestamps. For a particular event E_c, PE is the period of the event if,

$$E_c.\text{timestamp} = E_c.(\text{timestamp} + \text{PE}) \tag{3.3}$$

3.2.3.2 Event classifier

The analytics module also uses ED to determine the occurrence patterns of the events. The analytics module continuously analyzes the events, uses ED to determine its previous occurrences and detects whether an event is periodic or not. The module classifies each event into two categories: (1) periodic and (2) aperiodic. If the event takes place without maintaining any consistency, it can be categorized as an aperiodic event. When an event takes place after a fixed interval, we define the event as periodic. For a periodic event, the analytics module also determines its periodicity.

3.2.3.3 Characterization of situations

For each event, we store its state, location, speed, duration, and periodicity (for the aperiodic event, the periodicity value is zero). At a particular timestamp t_k, we characterize the environmental situation as the collection of events detected at that time as presented in Figure 3.1. In timestamp t_k, situation S_k can be represented as,

$$S_k = \overbrace{t_k, E_1, E_2, \ldots, E_d}^{\text{Situation}} \tag{3.4}$$

Where d is the number of detected events in situation S_k, t_k is the timestamp when the situation was captured and $\{E_1, E_2, \ldots, E_d\}$ are the detected events at t_k.

Chapter 4

Mapping situations to tasks in the situation-aware real-time system

4.1 Introduction

A situation-aware RTS needs to have sufficient knowledge of its situations and its subsequent changes, which can be obtained from the environmental input stream [45]. It is necessary for the system to have a prior knowledge of its interactions with various objects of the environment involving different timing constraints to ensure safe and correct operations. It is also essential for the system to extract timing properties by mining environmental input data, and understand the flow of execution by creating a knowledge-base. Therefore, one of the aims of the situation-aware RTS is to create a knowledge-base from the monitored environmental input stream that will consume significantly less memory, allow faster information processing, and help to identify, analyze and validate safety, performance as well as adaptive aspects.

4.2 Workflow of the situation-aware real-time system

The complexity of existing RTS and available adaptive behaviors have led the RTS research community to investigate innovative ways of designing and developing a situation-aware RTS which can assure functional as well as timing guarantees at runtime. The RTS can undergo a number of interactions with various objects of the environment which create challenges for predicting and assuring the runtime behavior. Failures of such system at runtime can result in death, potential harm to property, or the environment [46].

For the RTS, situation-awareness is emerging as a necessary underlying ability which creates the necessity for designing innovative ways to ensure its smooth operation at runtime.

4.2.1 Monitoring the environment of the real-time system

Monitoring the environmental situations of the RTS [47] is useful for validating the functional and timing requirements of RTS. Interestingly, monitoring can gather information about the environment which is essential to investigate uncertainties [48] towards building an intelligent RTS that has sufficient knowledge of all the possible interactions. The RTS can use the environmental input stream gathered from the monitored environment to identify data patterns [48] which can help in characterizing the situations including the uncertainties of the system environment.

4.2.2 Characterizing environmental situation

One of the objectives of the proposed situation-aware RTS is to characterize the environmental situation which includes identification of real-world occurrences as events from mining the monitored environmental input stream and analyzing their properties. The properties of the events also allow us to create a knowledge-base which presents information about historical as well as current environmental situations in terms of events (along with their properties and relationships involved among them). It also facilitates faster information retrieval and processing, allowing the RTS to compute a significant amount of environmental information with limited overload.

4.2.2.1 Identifying objects and events

The initial steps for characterizing environmental situation involve the identification and classification of objects from the environmental input stream obtained from different sensors. We perform sensor fusion to combine and identify the objects present in the RTS environment. An identified object O_b, in our work, can be defined as follows:

$$
\begin{array}{|l}
\hline
\textit{Object}, O_b \\
\hline
id : \mathbb{N} \\
timestamp : \mathbb{N} \\
location : \mathbb{R} \\
state : \mathbb{N} \\
speed : \mathbb{R} \\
\hline
timestamps \geq 0 \\
speed \geq 0 \\
\hline
\end{array}
$$

For each object O_b, the situation-aware RTS records the information which includes the unique identification number of the object, the recorded time, location, state (moving or static object) and the speed of the object.

To determine any changes or modification of the objects in the current environmental input, for each arriving environmental input, the situation-aware RTS compares each object O_b in I_{n+1} with its previous condition in I_n. If the difference is less than some predefined threshold, the situation-aware RTS assumes that the object did not undergo any significant modification or change. However, if the difference is more than the threshold value, the situation-aware RTS detects the degree of alteration for the particular object. Therefore, any change in the behavior of the object can be tracked. Such tracking enables the situation-aware RTS to update the properties of the objects with time demonstrated as follows:

$$
\begin{array}{|l}
\hline
\textit{UpdateObject}, O_b \\
\hline
\Delta \textit{Object} \\
changed\_timestamp? : \mathbb{N} \\
changed\_location? : \mathbb{R} \\
changed\_state? : \mathbb{N} \\
changed\_speed? : \mathbb{R} \\
\hline
timestamp' += changed\_timestamps \\
location' += changed\_location \\
state' = changed\_state \\
speed' += changed\_speed \\
\hline
\end{array}
$$

4.2.2.2 Analyzing the properties of the events

To ensure that the timing constraints are adequately met, the situation-aware RTS extracts real-time properties of the system, associated with each event as presented in

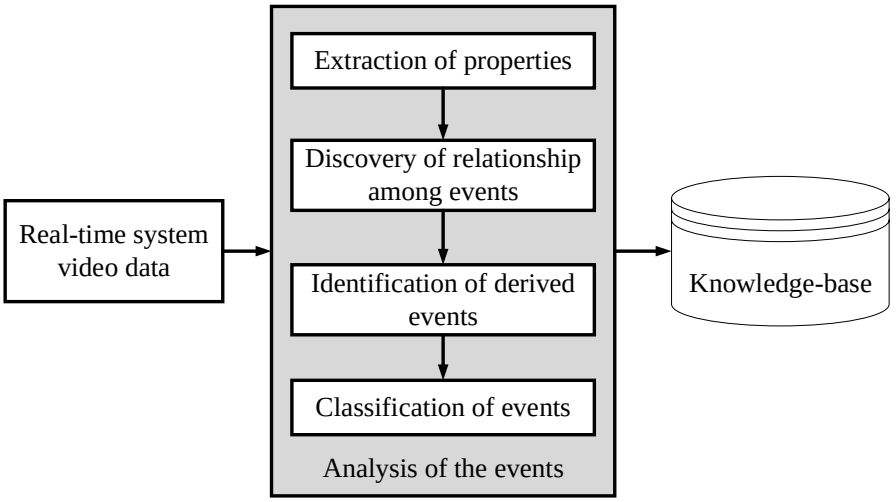


FIGURE 4.1: Identification and analysis of the properties of events

Figure 4.1. We define a temporal dataset called ED, which uses the updated information associated with an object O_b and stores its states and properties for each $I_k \in I$. Therefore, ED keeps track of various activities associated with each object, which serves as the basis of event detection. The situation-aware RTS uses ED to identify an event E_c associated with an object O_b. For each event E_c, the situation-aware RTS identifies the start time of the event and determines its duration using ED. The situation-aware RTS also perform continuous analysis of the detected events on ED and capture the appearances of events in different timestamps.

$$
\begin{array}{|l}
\hline
\textit{Event}, E_c \\
\hline
id : \mathbb{N} \\
interactingObject : \mathbb{P}\ Object \\
startTime : \mathbb{N} \\
endTime : \mathbb{N} \\
duration : \mathbb{N} \\
location : \mathbb{R} \\
speed : \mathbb{R} \\
type : \mathbb{P}\ periodic, aperiodic \\
\hline
duration = endTime - startTime; \\
\hline
\end{array}
$$

Event E_c contains information regarding the events associated with each object. The situation-aware RTS uses E_c to keep track of the changes of the event in terms of position and state with respect to time.

4.2.2.3 Identifying the relationships involved among events

Apart from the detection of the events associated with different objects, the situation-aware RTS also identifies those events that are the results of interactions between two or more events as shown in Figure 4.1. The situation-aware RTS classifies the events as basic set of events called E_{basic} and derived set of events called $E_{derived}$. Derived events occur because of the interactions among the basic events. The situation-aware RTS contains a dataset called AR which contains the association relationships among the E_{basic} and $E_{derived}$. Each row $AR_i \in AR$ contains a set of events E (that are in association with each other) and a rule, which has the following form,

$$E_{basic} \Rightarrow E_{derived}, \text{ Where } E_{basic}, E_{derived} \subseteq E$$

Each row $AR_i \in AR$ represents a rule in terms of events. However, from all rules in AR, the situation-aware RTS identifies the rules which are valid and selects them while determining the derived events. Hence, for each set of event E_{basic}, the situation-aware RTS identifies its frequency in AR using the function $fr(E_{basic})$ which can be represented as,

$$fr(E_{basic}) = \frac{\left|\{AR_i \in AR;\ E_{basic} \subseteq AR_i\}\right|}{|AR|} \tag{4.1}$$

For each rule, the situation-aware RTS uses AR to identify how often the rule was evaluated as true using the confidence value. The situation-aware RTS calculates the confidence value $conf(E_{basic} \Rightarrow E_{derived})$ as the ratio of the transactions which contain E_{basic} with the transactions containing $E_{derived}$.

$$conf(E_{basic} \Rightarrow E_{derived}) = \frac{fr(E_{basic} \cup E_{derived})}{fr(E_{basic})} \tag{4.2}$$

For each rule, the situation-aware RTS also identifies a conviction value. The conviction value $conv(E_{basic} \Rightarrow E_{derived})$ can be defined as the ratio of the frequency where E_{basic} takes place without $E_{derived}$ (i.e., the possibility of making an incorrect prediction).

$$conv(E_{basic} \Rightarrow E_{derived}) = \frac{1 - fr(E_{derived})}{1 - conf(E_{basic} \Rightarrow E_{derived})} \tag{4.3}$$

From all possible rules, the situation-aware RTS considers only those rules that satisfy a minimum confidence value and maximum conviction value. The rules which satisfy the thresholds is considered as the set of final rules and stored in AR to determine the

derived events at runtime. An event must take place if every other event it is associated with takes place.

Example 4.1. ***Derived event:*** *Assume a row of* AR *contains events* E_1, E_2, E_3 *and* E_4 *associated with each other. The situation-aware RTS concludes that event* E_4 *(although it may be undetected) must take place if we detect* E_1, E_2 *and* E_3. *In this case* E_1, E_2 *and* E_3 *can be termed as basic events and* E_4 *can be identified as derived events.*

UpdateEvent, E_i

$\Delta Event$

$changed\_timestamps? : \mathbb{N}$

$changed\_location? : \mathbb{R}$

$timestamps' += changed\_timestamps$

$location' += changed\_location$

4.2.3 Creating the knowledge-base

Data helps us in understanding the patterns and relationships involved among the detected events from the environment of an RTS. The RTS can identify the safety and performance constraints as well as analyze the historical and current information to make a deterministic prediction of its future conditions. Therefore, it is necessary to generate a knowledge-base which describes the environment of the RTS in terms of events. It is also required to ensure that the generated knowledge-base consumes significantly reduced memory and allows faster computation such that it is suitable for the RTS. Our proposed formation of a knowledge-base scheme is presented as follows:

- For each input I_k, the situation-aware RTS identifies all the events using temporary data called ED defined in Equation 3.1.
- For each event E_c, the situation-aware RTS uses the operational environment model to extract its properties and determines whether it is a newly arrived event or an existing event.
- For each existing event, the situation-aware RTS determines its type (periodic or aperiodic). In case of periodic events, the module determines its periodicity.
- The situation-aware RTS uses AR to detect derived events from basic events.
- The situation-aware RTS presents a knowledge-base which is called KB as shown in Figure 4.1.

- If the detected event is newly arrived or aperiodic, the situation-aware RTS stores its information (along with its properties) in KB.
- If the event is periodic, the situation-aware RTS avoids storing the event (as its first occurrence is already stored).
- If the event is a derived event, consisting of a combination of basic events, the situation-aware RTS avoids storing the basic events which are already stored.

The situation-aware RTS identifies the current location of the events, and by comparing with the past event information, determines their speed and next predicted position. Apart from the detected event, the situation-aware RTS uses ED and AR formed to identify the derived events that are the result of existing events. The situation-aware RTS forms a knowledge-base called KB where it stores all the events detected in each timestamp of environmental input arrival. In the generated knowledge-base KB, k^{th} row, KB_k can be given as,

$$KB_k = [t_k, E_1, E_2, \ldots, E_d] \tag{4.4}$$

Where, d is a positive natural number denoting the number of events detected in t_k. Here t_k is the timestamp of environmental input arrival and $\{E_1, E_2, \ldots, E_d\}$ is the set of detected events at that timestamp. Since the RTS considered in this work is embedded in nature, we put a limit on the number of timestamps can be stored in KB. Therefore, the KB contains a user-defined number of most recent timestamps. In other words, KB can be considered as a queue of situations where the situations are stored in KB using the First-In-First-Out replacement policy. In this work, the maximum size of KB is 30,000.

4.2.4 Satisfying the user-defined constraints

The behavior of an RTS can be modeled by a discrete-time finite automaton (5) tuple, $(\mu, \Sigma, \omega, \mu_1, F')$, consisting of,

- A finite set of states or modes μ,
- A finite set of events called the alphabet (Σ),
- A transition function based on events ($\omega : \mu \times \Sigma \rightarrow \mu$),
- An initial state or mode ($\mu_1 \in \mu$), and

- A final state ($F' \in \mu$).

The validation framework of the situation-aware RTS determines the expected system mode $\mu_{\text{expected}} \in \mu$, checks whether the system is operating in the desired mode or not and triggers a verification action ω (if necessary). The RTS uses ω for switching the operating mode to μ_{expected} at runtime. To model the mode changes of the RTS, we define an event variable containing two event values, $\Sigma = \{\text{up}, \text{down}\}$. The transition functions are defined by,

1. $\text{safety} = \omega(\text{performance}, \text{up})$
2. $\text{performance} = \omega(\text{safety}, \text{down})$

4.2.5 Identifying adaptive tasks in a particular situation

In this thesis, we identify additional adaptive tasks obtained from the environmental situations at runtime. For each situation, the RTS identifies the environmental events and determines their properties (such as duration, location, speed, and periodicity). Therefore, the RTS can collect information on the system behavior at runtime through monitoring and allows characterization of behavior regarding each experienced situation. For each situaion S_k, Algorithm 2 uses the procedure IdentifyAdaptiveTasks(S_k) to identify a set of d events associated with different objects $S_k = \{E_1, E_2, \ldots, E_d\}$. Each event, in our work, can be categorized into one of discrete categories $\gamma = \{\gamma_1, \gamma_2, \ldots, \gamma_g\}$. The procedure IdentifyAdaptiveTasks(S_k) identifies the unique visited catogories assiocited with the events detected in S_k.

Each event category γ_i corresponds to a particular adaptive task τ_i. The procdure FindAdaptiveTasks(γ_i) in Algorithm 2 performs decision rule learning (from line 16 to 21) and identifies the adaptive taskset associated with the events and uses procedure FindDepandantTasks(τ_i) to identify the dependant tasks.

We define a dataset called PR which contains precedence relationship $\tau_i \Rightarrow \tau_j$ (denotes every occurrence of τ_j must be preceded by τ_i) among the adaptive tasks. For each identified tasks τ_{out_i}, we also use PR to identify addition adaptive tasks which precede τ_{out_k}. Therefore, for a particular situation S_k, Algorithm 2 identifies the adaptive tasks $\tau_{\text{out}}^{S_k}$ which are needed to be executed.

Algorithm 2 Identify adaptive tasks from a situation.

procedure IDENTIFYADAPTIVETASKS(S_k)
  $\tau_{out}^{S_k} \leftarrow \varnothing$
  VisitedEventCategory $\leftarrow \varnothing$
  for each Event $E_j \in S_k$ **do**
    $\gamma_j \leftarrow$ Occurrencecategory(E_j)
    γ_j.visited $\leftarrow$ Find(VisitedEventCategory, γ_j)
    if γ_j.visited = false **then**
      FindAdaptivetasks(V, v_j)
      VisitedEventCategory.add(γ_j)
    end if
  end for
end procedure
procedure FINDADAPTIVETASKS(γ_i)
  $\tau_{adaptive} \leftarrow \varnothing$
  $f(\gamma_i) = \left|\{TD_i \in TD;\ \gamma_i \subseteq TD_i\}\right| / |TD|$
  for each task $\tau_i \in \tau_{out}$ **do**
    $cf(\gamma_i \Rightarrow \tau_i) = f(\gamma_i \cup \tau_i)/f(\gamma_i)$
    $cv(\gamma_i \Rightarrow \tau_i) = (1 - fr(\tau_i))/(1 - cf(\gamma_i \Rightarrow \tau_i))$
    if $cf \leq FH \wedge cv \leq VH$ **then**
      $\tau_{adaptive} \leftarrow \tau_{adaptive} \cup$ FindDepandantTasks(τ_i)
    end if
  end for
  return $\tau_{adaptive}$
end procedure
procedure FINDDEPANDANTTASKS(τ_i)
  τ_i.visited $\leftarrow$ true
  for each Vertex $\tau_j \in PR[\tau_i.Parent]$ **do**
    if τ_j.visited = false **then**
      FindDepandantTasks(τ_j)
    end if
  end for
  return $\tau_{dependant} \cup \tau_j$
end procedure

4.2.6 Execution model of the proposed situation-aware real-time system

The proposed situation-aware RTS contains two types of execution model which are non-adaptive and adaptive execution models as presented in Figure 4.2.

1. Non-adaptive execution model: In non-adaptive execution model, the RTS executes only tasks from internal task set characterized by current mode. The RTS can use a scheduler characterized by a scheduling algorithm called SA_1 such that $SA_1 : \tau_{in}^{\mu_{current}} \rightarrow Pr$ (assigns and executes each task $\tau_i \in \tau_{in}^{\mu_{current}}$ using a processor Pr) as illustrated by Figure 4.2. In this work, we consider $SA_1 = EDF$, (i.e. the non-adaptive execution model

uses the EDF scheduling algorithm) for scheduling the internal tasks.

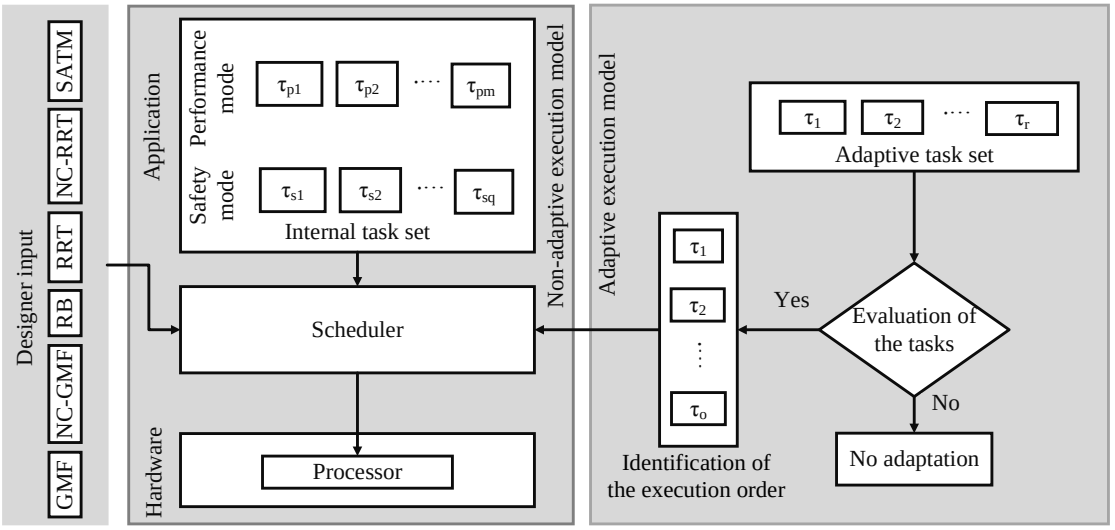


FIGURE 4.2: Execution model of the situation-aware RTS

2. Adaptive excution model: In adaptive execution model, we identify events in different situations and execute adaptive tasks in response to the events that take place in the RTS environment. The adaptive execution model is characterized by a scheduling algorithm $\mathrm{SA}_2 : \{\tau_{\mathrm{in}}^{\mu_{\mathrm{current}}} \cup (\tau_{\mathrm{out}} \subseteq \mathrm{G})\} \rightarrow \mathrm{Pr}$ such that it assigns the both the internal and the adaptive task $\tau_{\mathrm{i}} \in \{\tau_{\mathrm{in}}^{\mu_{\mathrm{current}}} \cup \tau_{\mathrm{out}}\}$ in processor Pr in order to execute all the tasks. Figure 4.2 shows that the RTS designer can select any task model from $\{\mathrm{GMF}, \mathrm{NC-GMF}, \mathrm{RB}, \mathrm{RRT}, \mathrm{NC-RRT}, \mathrm{SATM}\}$ for the execution of adaptive tasks.

4.2.7 Using existing task models to execute adaptive tasks

Our execution model allows the tasks to be included in the existing task model if the schedulability analysis associated with the task model are met.

One of the primary challenges in developing these models is their analytical complexity. More specifically the graph-based models are difficult to analyze. For a set of adaptive tasks τ_{out}, the adaptive execution model presented in Figure 4.2 calculates the accumulated worst-case execution demand $\mathrm{rf}_{\tau_{\mathrm{out}}}(\delta)$ of τ_{out} that can be released in δ due to the events detected in $\mathrm{S_k}$. The adaptive execution model allows the designer to select any one task model from $\{\mathrm{GMF}, \mathrm{NC-GMF}, \mathrm{RB}, \mathrm{RRT}, \mathrm{NC-RRT}, \mathrm{SATM}\}$. For each selected task model, we perform a schedulability test using their respective feasibility analysis procedure defined in [49]. The adaptive execution model allows the selected task model to execute the adaptive task τ_{out} identified in $\mathrm{S_k}$, if τ_{out} pass the schedulability test.

4.3 Proposed situation-aware graph-based task model

We present SATM, which allows the execution of adaptive tasks in different environmental situations. Each task can be added to the proposed SATM dynamically as a vertex and the execution order between a pair of tasks as an edge. While including the adaptive tasks in SATM, we ensure timing requirements by defining a number of timing and graph-based constraints and include the vertices in the SATM, if the constraints are met. In a particular situation S_k, the adaptive tasks in SATM can be characterized by a directed acyclic graph $G(S_k)$ which can be defined as:

$$G(S_k) = (V, H) \text{ where,}$$

1. V is the set of vertices. For each S_k, the RTS needs to execute a set of adaptive tasks $\tau_{out}^{S_k} \in \tau_{out}$. Each task $\tau_{out_i} \in \tau_{out}^{S_k}$ is represented using a vertex $v_i \in V$.
2. Each vertex $v_i \in V$ can be defined as, $v_i = (\alpha_i, C_i, D_i)$.
3. H is the set of directed edges. Each edge (v_i, v_{i+1}) represents the order of execution of two tasks $(\tau_{out_i}, \tau_{out_{i+1}})$.

4.3.1 Characterizing adaptive tasks using SATM

For each situation S_k, we identify the set of vertices $V = \{v_1, v_2, \ldots, v_r\}$ needed to be executed in response to events detected in S_k by performing decision rule learning. For each event E_j in S_k, we identify the vertex $v_i \in V$ needed to be executed. We identify whether v_i is already included in the SATM. We define a set called CV which stores the vertices that can potentially be added to the SATM in the current situation. If v_i is absent in the SATM and CV, we add it to CV. We use PR to identify the vertices which precede v_i and also add them to CV. Other events which have the same occurrence pattern can also be translated to the same adaptive task. Hence for a particular situation S_k, we identify the set of tasks $\tau_{out}^{S_k}$ which are needed to be executed.

4.3.2 Evaluating timing constraints

A task must complete its execution within a specific time bound. Hence, it is essential for the RTS to define and evaluate various timing constraints associated with each vertex before including it in the SATM. The constraints are described as follows:

1. **Deadline constraint,** $TC_1(v_i)$**:** Each vertex v_i must finish its execution before the deadline D_i.

$$C_i \leq D_i \tag{4.5}$$

2. **Real-time task order,** $TC_2(v_i, v_{i+1})$**:** A vertex v_i can precede (execute before another) another vertex v_{i+1} iff, the relative deadline of v_i is less than or equals to the the relative deadline of v_{i+1}.

$$D_i \leq D_{i+1} \tag{4.6}$$

3. **Range,** $TC_3(v_i)$**:** The worst-case execution time demand of vertex v_i must satisfy range $T_{available}$ defined in Equation 4.

$$\theta(\tau_{in}) = \sum_{i \in q} C_i \tag{4.7}$$

$$T_{available} = \delta - \theta(\tau_{in}) \tag{4.8}$$

4. **Estimated duration,** $TC_4(v_i)$**:** The estimated duration $\Delta(v_i)$ for each vertex $v_i \in V$ must be less than $T_{available}$.

$$\Delta(v_i) \leq T_{available} \tag{4.9}$$

For a set of tasks to be evaluated as correct, no timing constraints can be violated which we define as TC. Therefore, for each situation S_k, evaluation of the timing constraints associated with each vertex $v_i \in V$ can be represented as,

$$TC_1(v_i) \wedge TC_2(v_i, v_{i+1}) \wedge TC_3(v_i) \wedge TC_4(v_i) \vDash TC \tag{4.10}$$

4.3.3 Evaluating graph-based properties

Graph-based properties, GC: During the formation of the SATM, the mapped vertices must follow some graph-based properties which are described below:

GC_1**:** A pair of vertices (v_i, v_{i+1}) can form an edge if they satisfy Equation 4.11.

$$D_{i+1} - C_{i+1} - \alpha_{i+1} \geq D_i - C_i - \alpha_i \tag{4.11}$$

We identify the execution order of CV in the decreasing order of their respective relative deadlines (using line 17 of Algorithm 5) associated with S_k as path $\pi(S_k)$ which can be expressed as:

$$\overbrace{v_1 \xrightarrow{(v_1,v_2)} v_2 \xrightarrow{(v_2,v_3)} \dots v_{o-1} \xrightarrow{(v_{o-1},v_o)} v_o}^{\pi(S_k)}$$

The length of the path $\pi(S_k)$ can be written as,

$$\text{Length}(\pi(S_k)) = \sum_{v_i \in \pi(S_k)} C_i + \alpha_i \tag{4.12}$$

Distance $\text{dist}(v_i, v_j)$ is the minimum distance of the vertex from $v_i \in CV$ to $v_j \in CV$. The diameter of the SATM as the maximum distance between the two vertices (in terms of execution time) of G,

$$\text{diam}(G(S_k)) = \max_{(v_i,v_j)\in H} \text{dist}(v_i, v_j) \tag{4.13}$$

GC_2**:** In the SATM, $\text{diam}(G(S_k))$ must be less than δ,

$$\text{diam}(G(S_k)) \leq \delta \tag{4.14}$$

GC_3**:** A set of vertices CV can be added to the existing execution path $\pi(S)$ in the graph if,

$$\text{Length}(\pi(S)) + \text{rf}_V(\delta) \leq \delta \tag{4.15}$$

We also avoid including the vertices which violate the constraints GC_1, GC_2, and GC_3. We use the Procedure $\text{FindVertex}(G(S_k), v_i)$ in Algorithm 3 to identify whether a vertex $v_i \in CV$ is already included in $G(S_k)$ or not. If the vertex is absent in $G(S_k)$, Algorithm 5 adds the vertex v_i in the SATM. Otherwise, Algorithm 5 merges the vertex in $G(S_k)$ using the Procedure MergeExecutionPath(CV) presented in Algorithm 4. If a task is already present in the SATM, the Algorithm 4 uses the Procedure $\text{Merge}(\tau_i, \tau_j)$ which finds and merges the task τ_i with the task τ_j. If the task is absent in the current SATM, the Procedure $\text{Add}(\tau_i, \text{SATM})$ in Algorithm 4 adds the task τ_i to the SATM.

Algorithm 3 Find Vertex in SATM.

```
1: procedure FindVertex(G(S_k), v_i)
2:     v_i.visited ← true
3:     for each Vertex v_j ∈ G(S_k).Adj[v_i] do
4:         if v_j.visited = false then
5:             FindVertex(G(S_k), v_j)
6:         end if
7:     end for
8:     return v_j
9: end procedure
```

4.3.4 Identifying the execution order of adaptive tasks

For each new event, if the mapped vertex is already included in CV, we avoid including the vertex in CV. In other words, events considered in this work can be categorized into one of the discrete categories γ. Each event category $\gamma_k \in \gamma$ corresponds to a particular occurrence pattern which can be mapped to one particular adaptive task. Hence, multiple events in S_k can be mapped to one particular task.

Algorithm 4 Merge adaptive tasks in Existing task model.

```
1: procedure MergeAdaptiveTasks(τ_out^{S_k})
2:     for each task τ_i ∈ τ_out^{S_k} do
3:         τ_i.visited ← false
4:     end for
5:     for each task τ_i ∈ τ_out^{S_k} do
6:         if (τ_j ← FindVertex(τ_out^{S_k}, τ_i)) then
7:             Merge(τ_i, τ_j)
8:         else
9:             Add(τ_i, TaskModel)
10:        end if
11:    end for
12: end procedure
```

For example, consider that the automotive system specified in Example 3.1 identifies two events in a particular situation such as 1) movement of a pedestrian from one side of the road to another, and 2) the change of a traffic signal from yellow to red. These two events can be translated to one adaptive task in the automotive system which is "Braking." Therefore, CV contains the vertices which are needed to be executed in S_k. Since multiple events can be mapped to one particular task, the number of vertices in CV is less than or equal to the number of tasks in $\tau_{out}^{S_k}$.

Algorithm 5 illustrates the step by step procedure of identifying the execution order of CV. We use the respective relative deadlines of all the vertices to assign priorities (in

the decreasing order of the relative deadlines). We evaluate each vertex $v_i \in CV$ using the timing constraints (in line 6 to 9) before including it into the SATM. Line 15 of Algorithm 5 also evaluates the vertices using a number of graph-based constraints. If any vertex $v_i \in CV$ violates the timing or graph-based constraints, we avoid including CV in the SATM. However, if the set of vertices CV satisfy all the constraints, we update the SATM where we include CV in the existing SATM.

Algorithm 5 Formation of SATM.

```
1:  procedure FindExecutionOrder(S_k)
2:      {v_1, v_2, ..., v_o} <--Identifyadaptivetasks-- S_k
3:      OV ← {v_1, v_2, ..., v_o}
4:      OrderedVertices ← SortVerticesByDeadline(OV)
5:      for each Vertex v_i ∈ OrderedVertices do
6:          TC_1 ← Evaluate(C_i ≤ D_i)
7:          TC_2 ← Evaluate(D_i ≤ D_{i+1})
8:          TC_3 ← Evaluate((T_available = δ − θ(τ_in)) ≥ 0)
9:          TC_4 ← Evaluate(T_available ≤ C_i)
10:         if TC_1(v_i) ∧ TC_2(v_i, vi + 1) ∧ TC_3(v_i) ∧ TC_4(v_i) = false then
11:             return
12:         end if
13:         v_i.child ← v_{i+1}
14:     end for
15:     if GC_1 ∧ GC_2 ∧ GC_3 = false then
16:         return
17:     else
18:         MergeExecutionPaths(OrderedVertices)
19:     end if
20: end procedure
```

Lemma 4.1. *For the given set of vertices* CV *associated with* S_k*, the length of the path* $\pi(S_k)$ *in* $G(S_k)$ *must be less than the time interval* δ*,*

$$\text{Length}(\pi(S_k)) \leq \delta \tag{4.16}$$

Proof: Let us assume that the proposition presented in Equation 4.16 is false. The conditional expression being false means that for S_k, we obtain the length of $\pi(S_k)$ as,

$$\text{Length}(\pi(S_k)) > \delta \tag{4.17}$$

However, the constraint GC_2 states that even the maximum distance between any two vertices $\text{diam}(G(S_k))$ in $G(S_k)$ must be less than or equals to δ. Therefore, the length of $\pi(S_k)$ which is given as $\text{Length}(\pi(S_k)) > \delta$ must violate the constraint GC_2. Therefore,

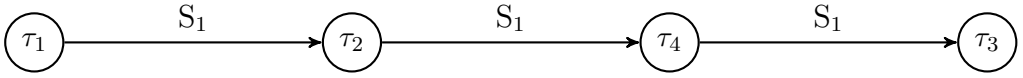
path $\pi(S_k)$ for which conditional expression 4.17 is true cannot exist in the SATM. Thus the proposition presented in Equation 4.16 must be true.

Lemma 4.2. *A new path $\pi(S_k)$ can be merged to an existing execution path $\pi(S)$ in the graph if,*

$$\text{Length}(\pi(S)) + \text{Length}(\pi(S_k)) \leq \delta \tag{4.18}$$

Proof: Merging the execution paths in Algorithm 5 consist of two cases. Case one involves finding and matching the vertices which are present in both $\pi(S_k)$ and $\pi(S)$. In this case, since no new vertices are added in path $\pi(S)$ we have,
$\text{Length}(\pi(S)) + \text{Length}(\pi(S_k)) = \text{Length}(\pi(S))$. Hence, using Lemma 1, we can state that the overall length of the execution path $\text{Length}(\pi(S))$ is less that δ.
Case two includes those vertices which are present in $\pi(S_k)$, but absent in $\pi(S)$ and thereby requires the addition of new vertices. From GC_3, we see that adding new vertices in the existing path $\pi(S)$ also keeps the overall length less than δ.

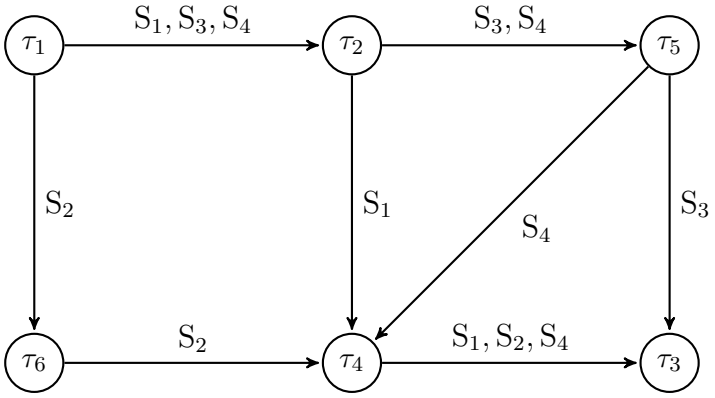
Example 4.2. ***Formation of SATM:*** *Assume that, we capture a situation S_1 at runtime. Also, consider that the system needs to execute adaptive tasks $(\tau_1, \tau_2, \tau_3, \tau_4)$ in response to S_1 with relative deadlines $(2, 9, 37, 18)$ respectively. Our system constructs a SATM which contains each task as vertex and flow (order) of execution between them as edges. Therefore, it constructs the graph model which executes the tasks in $(\tau_1 \rightarrow \tau_2 \rightarrow \tau_4 \rightarrow \tau_3)$ order.*



Additionally, consider that we obtain new situations at runtime which are associated with following adaptive tasks,

- $S_2 = (\tau_1, \tau_6, \tau_4, \tau_3)$
- $S_3 = (\tau_2, \tau_1, \tau_3, \tau_5)$
- $S_4 = (\tau_2, \tau_1, \tau_4, \tau_5, \tau_3)$

If the tasks τ_5, and τ_6 have relative deadlines 32, and 5 respectively, then the final SATM in after receiving S_4, in this example can be visualized as,



In the SATM, for each situation in which the adaptive tasks have satisfied the constraint, we update the SATM by including the vertices associated with the situation as the new vertices as presented in Algorithm 5. With the arrival of a new situation S_k at time $t_k \in T$, we determine the overload of the internal tasks τ_{in} at first and calculates the worst-case estimated duration for the internal tasks as, $\theta(\tau_{in})$. In this work, we consider the frame arrival time t_k as the scheduling point and schedule the ready tasks in time interval δ (supply).

4.3.5 Schedulibility analysis of adaptive tasks for each situation

Theorem 4.3. *If the initial input to Algorithm 5 is* $G(S_k)$ *and the finally constructed SATM is* $G(S'_k)$ *then,*

$$\text{Length}(\pi(S_k)) \geq \text{Length}(\pi(S'_k))$$

Proof: Consider that CV is the set of vertices obtained at runtime and CV′ is the set of vertices which satisfies the constraints. Assume that, the RTS avoids execution of r number of adaptive tasks from the given situation where $(r \geq 0)$ which can be represented using adaptive task set, $v_r = v_i : (0 \leq r \leq \text{card}(CV'))$. Therefore, we have,

$$CV = CV' \cup v_r \tag{4.19}$$

The cardinality of these task sets can be viewed as:

$$\text{card}(CV) = \text{card}(CV') + \text{card}(v_r)$$
$$\Rightarrow \text{card}(CV) \geq \text{card}(CV')$$

From the above expression, we view that system avoids execution of v_r form a set of $G(S_k)$ vertices and executes $G(S'_k)$ tasks.

$$\Delta(CV) = \sum_{v_i \in CV} C_i,\ \Delta(CV') = \sum_{v_j \in CV'} C_j,\ \Delta(v_r) = \sum_{v_k \in v_r} C_k$$

Hence, Equation 4.19 can be written as,

$$\Delta(CV) = \Delta(CV') + \Delta(v_r)$$
$$\sum_{v_i \in CV} C_i = \sum_{v_j \in CV'} C_j + \sum_{v_k \in v_r} C_k$$

Since all the vertices are associated with the events captured from the same situation, they have the same arrival time. So the above expression can be rewritten as,

$$\sum_{v_i \in CV} C_i + \alpha_i = \sum_{v_j \in CV'} C_j + \alpha_j + \sum_{v_k \in v_r} C_k + \alpha_k$$
$$\text{Length}(\pi(S_k)) = \text{Length}(\pi(S'_k)) + \text{Length}(\pi(v_r))$$

The vertex set v_r has positive or zero number of vertices. Therefore, each vertex $v_i \in v_r$ has a computation time C_i which is greater than zero. The respective execution paths associated with the vertices can be represented as,

$$\text{Length}(\pi(S_k)) \geq \text{Length}(\pi(S'_k))$$

Theorem 4.4. *At a particular situation S_k, with time interval δ, a set of tasks $\tau = \tau_{in} \cup G(S_k)$ which are being executed using SATM, are uniprocessor feasible.*

Proof: From [14] we know that, a set of tasks τ_{in} is uniprocessor feasible in a time interval δ, if $\text{dbf}_{\tau_{in}}(\delta) < \delta$. For each δ, a given set of vertices CV can be scheduled after scheduling all the internal tasks in the $T_{available}$ time slots. Similarly, we know that a set of vertices $G(S_k)$ is uniprocessor feasible in time interval $T_{available}$ if,

$$\text{rf}_{G(S_k)}(\delta) \leq T_{available} \tag{4.20}$$

To be considered for execution using SATM, in our work, both internal and adaptive tasks, for a given situation S_k must satisfy, $T_{available} + \theta(\tau_{in}) \leq \delta$ to be scheduled in a

processor. Hence, the set of tasks $\tau = \tau_{\text{in}} \cup \text{G}(\text{S}_\text{k})$ we have,

$$\text{dbf}_{\tau_{\text{in}}}(\delta) + \text{rf}_{\text{G}(\text{S}_\text{k})}(\delta) \leq \delta \tag{4.21}$$

Hence, the combined execution demand associated with the internal and adaptive tasks never exceeds the supply. Therefore, set of tasks $\tau = \tau_{\text{in}} \cup \text{G}(\text{S}_\text{k})$ are uniprocessor feasible.

4.4 Discussion

For each situation S_k, the SATM schedules the internal tasks τ_{in} at first. Additionally, the RTS uses the SATM to identify and execute the adaptive tasks τ_{out} to the available slots $\text{T}_{\text{available}}$. Therefore, the overall demand (for both internal and adaptive tasks) is always less than or equals δ (maximum supply). If the tasks associated with the events satisfies the timing constraints and are already included in the SATM, then the execution model uses the SATM to execute the tasks at runtime. If the tasks are absent in the SATM, it avoids executing them at that time, stores their information and performs an update on the SATM. The formation and update of SATM, in this thesis, are performed offline because we consider handling the learned situation after tasks associated with the situation are added to the task model.

Chapter 5

Analyzing user-defined constraints for the situation-aware real-time system

5.1 Introduction

In this Chapter, we present a validation framework that identifies the expected mode at runtime and checks whether the situation-aware RTS is operating in the correct mode or not. To determine the expected mode, the validation framework identifies the safety constraint by determining the probability of failure in each environmental situations and uses the probability of failure of the system to determine the expected mode in different environmental situations.

The user-defined constraints of a situation-aware RTS must be guaranteed at runtime. Therefore, it is necessary for the RTS to form a knowledge-base which consumes a reduced memory and provides an improved decision-making ability (in comparison to raw environmental input stream). The knowledge-base can be used to identify the safety and performance of the system in different environmental situations. The goal of this chapter is to present a validation framework which identifies the expected operating mode, checks whether the system is operating in the expected mode or not, and triggers a verification action such that the RTS can satisfy the user-defined safety and performance constraints by switching its operating mode (if necessary) at runtime.

5.2 Identifying the safety constraint

In this thesis, we use KB to perform an analysis of the system from safety perspectives. To ensure that system states are safe, we perform a deductive failure analysis using fault tree. Fault tree of the automotive system mentioned in Example 3.1 is illustrated using Figure 5.1.

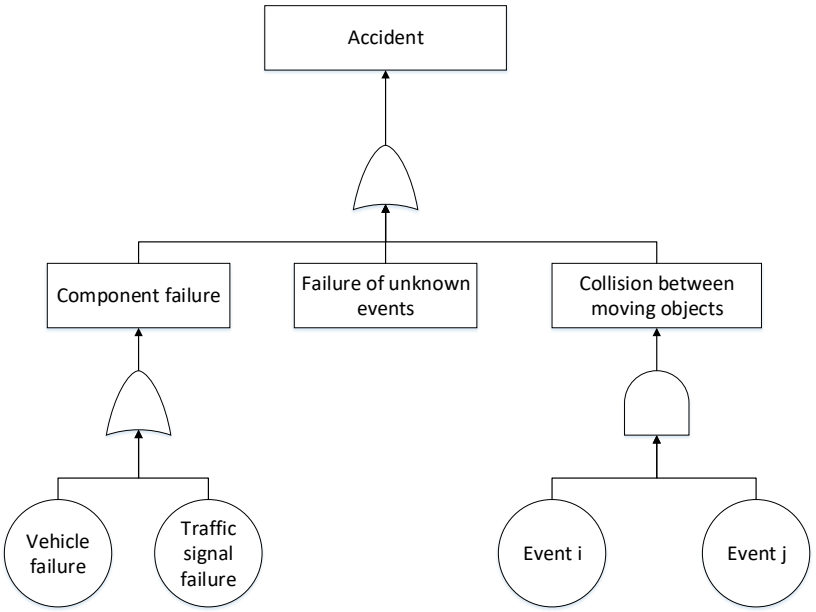


FIGURE 5.1: Our approach for RTS failure analysis using fault tree

A fault tree can be used to analyze one undesirable top event. For an automotive RTS, in Example 3.1, the top event can be defined as the occurrence of accidents. Once the top event is identified, now we need to determine the causes along with associated probabilities for the events. Those can be defined as intermediate events. For example, the reasons for an accident in an automotive system can be due to component failures or collision between two moving objects. However, these are the events that are the probabilistic result of some basic events.

In the automotive system scenario in Example 3.1 there might be some uncertain events. We use Bayesian techniques to estimate the likelihood of the failure of uncertain events and include them as an intermediate event in our fault tree. We determine, the probability of an uncertain event based on the moving events.

Let us assume, $P(E_{derived})$ is the probability of the unknown event $E_{derived}$. To calculate $P(E_{derived})$, we determine a total number of events that are in motion processed by

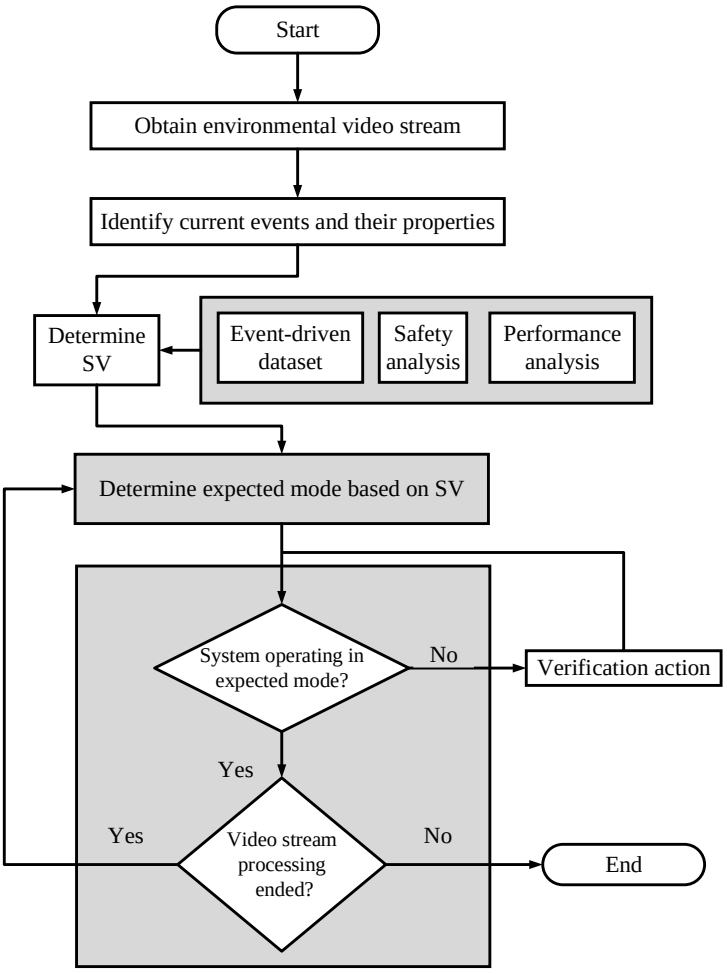


FIGURE 5.2: Workflow for generating expected behavior of the system using validation framework

the system using different time window. Our approach identifies maximum possible events for the systems. Therefore, we calculate $P(E_{derived})$ based on the number current events in motion with the all possible events. For our scenario, we consider that the uncertain events are the result of the moving events. We calculate the probability of an unknown event occurring of E_i given that $P(E_i)$ event already took place we implement a supervised learning algorithm based on the Bayes theorem. For the current set of events (both basic and derived) $E = \{E_1, E_2, \ldots, E_n\}$ we determine probability of unknown event $E_{derived}$ using the following relationship:

$$P(E_{derived} \mid E_1, \ldots, E_n) = \frac{P(E_{derived})P(E_1, \ldots E_n \mid E_{derived})}{P(E_1, \ldots, E_n)} \tag{5.1}$$

Using the naive independence assumption that

$$P(E_i \mid E_{derived}, E_1, E_2, \ldots, E_n) = P(E_i \mid E_{derived}), \tag{5.2}$$

For all i, Equation 5.1 can be simplified as

$$P(E_{derived} \mid E_1, \ldots, E_n) = \frac{P(E_{derived})\Pi_{i=1}^{n} P(E_i \mid E_{derived})}{P(E_1, \ldots, E_n)} \tag{5.3}$$

Since $P(E_1, \ldots, E_n)$ is constant given the input, we use the following classification rule:

$$P(E \mid E_1, \ldots, E_n) \propto P(E_{derived})\Pi_{i=1}^{n} P(E_i \mid E_{derived}) \tag{5.4}$$

$$\text{Or, } \hat{E_{derived}} = \arg\max_{E_{derived}} P(E_{derived})\Pi_{i=1}^{n} P(E_i \mid E_{derived}) \tag{5.5}$$

Our approach also takes failure probability of different components like vehicles or traffic signal into consideration as presented in Figure 5.1. Component failure in Example 3.1 can be classified as the failure of a traffic signal or failure in the vehicle system. For each time, we calculate the number of vehicles present in the environment. To calculate the probability of the failure of the components present at a particular time, we use the safety integrity level (SIL) that provide the safety standard, and failure probability provided calculated using a safety function [50].

For example, the vehicles running on a road are SIL 4 certified (the safest and dependable standard). As SIL 4 has a range of probability of failure (0.001 to 0.0001), we assume the heights value for our component (worst-case consideration) and deduct the chance of a failure for the system accordingly.

5.3 Identifying the performance constraint

In this section, we present an analysis of the performance of the system using KB. Our system uses a time interval, tw to capture various properties (performance) of the system. Initially, our system defines a variable called max and initializes it to zero. For each time interval, starting from beginning to situation arrival time (in milliseconds) we calculate currentload which can be given as the number of events processed in that time interval. We calculate, maximum load (max) by comparing loads of all the time intervals. Our performance analysis approach then selects a time interval, Selectedtimeinterval which contains a maximum number of events processed. For the Selectedtimeinterval, we make a comparison between the observed events in each time interval with *max* and determine the percentage of usage for the system. Our approach for determination of capacity usage can be demonstrated using the Algorithm 6.

Algorithm 6 Usage analysis of the system

```
1: max ← 0
2: usage ← 0
3: for tw = 1 to arrival time of video frames do
4:     for each tw ∈ total timestamp of video frame do
5:         currentLoad ← event processing time in tw
6:         if currentLoad > max then
7:             max ← currentLoad
8:             Selectedtimeinterval ← tw
9:         end if
10:        usage ← usage + currentLoad
11:    end for
12: end for
```

5.4 Identifying the expected mode

The validation framework uses the probability of failure value as presented in Figure 5.2 to identify the expected mode of operation. To identify the expected mode, the analytics module analyzes the knowledge-base and determines the safety constraint (probability of failure) using deductive failure analysis.

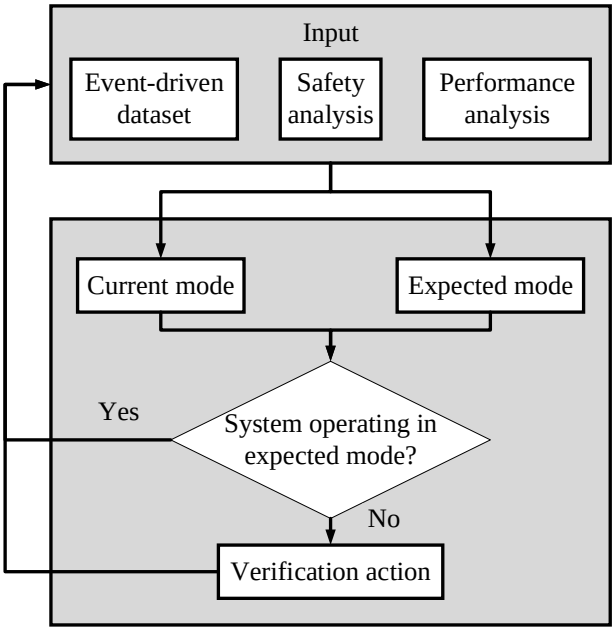


FIGURE 5.3: Validation framework

Based on our workflow described by Figure 5.2, we characterize the runtime behavior of the system in terms of the state machine. Each state in our work corresponds to a particular mode such as safety or performance. The transition from one state to another is dependent on a verification action called ω. To determine the expected modes of operation of the RTS, we define a threshold value called SV (which is the total

probability of failure) as illustrated in Figure 5.2. Figure 5.4 shows that the proposed RTS represents system states using two modes of operation namely performance and safety. Therefore, the transition between the states is defined by the SV. If the SV is less than some predefined threshold, then the validation framework considers the system to be safe (less probable to failure), and the expected mode of operation, in this case, is μ_2. However, when the SV exceeds the threshold, the model gives more preference on safety and expects the system to run in μ_1.

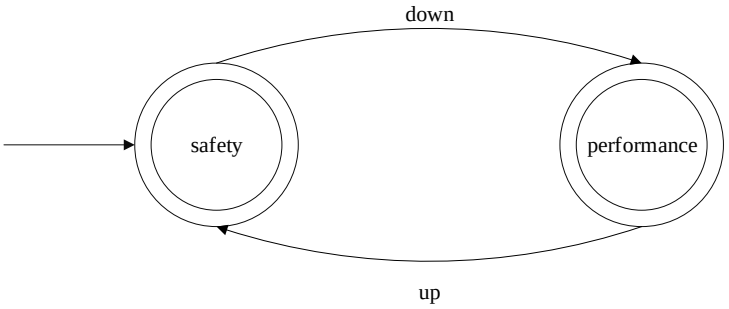


FIGURE 5.4: Mode switching in RTS

5.5 Satisfying the user-defined constraints

The RTS operates in a particular mode based on the current situation S_k. Each mode exhibits a different behavior than the other characterized by the set of tasks. With the change of a situation, guaranteeing functional behavior requires identification of the expected mode $\mu_{\text{expected}} \in \mu$ and execution of those specific tasks which satisfy μ_{expected}. For a given situation S_k, the RTS identifies tasks which can be any predefined reaction (to be executed based on the interactions) or any type of computation as specified by μ_{expected}. The adaptation process AN can be defined as changing the RTS behavior from μ_{current} to μ_{expected} at runtime.

$$\mu_{\text{current}} \xrightarrow{\text{AN}} \mu_{\text{expected}}$$

The validation framework aims at identifying the behavioral adaptation process AN which has the least migration steps to reach the expected behavior, μ_{expected}. To ensure the timing behavior during the adaptation process, the model defines multiple constraints which ensures that the RTS is safe, even during the adaptation process. The adaptation constraints associated with AN are defined as follows:

1. The deadline for all the RTS tasks must be maintained during the adaptation process AN.

2. The overload situation caused due to the adaptation process AN shall not cause any other tasks to miss their deadline.

3. The activation pattern and the execution of the periodic tasks must not be altered during the adaptation.

4. The RTS may need to provide emergency response to the environment due to any sudden change in a situation. In such cases, the associated tasks need to be executed as early as possible which might require executing the new task before or during the adaptation.

5. The adaptation process must not lead to any data corruption. In particular, it shall maintain consistency by not accessing half updated data.

For each time interval, we compare the expected mode and current mode of the system as presented in Figure 5.3. Figure 5.3 shows that the framework defines two verification actions based on the output $\{\text{Yes}, \text{No}\}$ and ensures the RTS to operate in the correct mode. The verification actions ω can be termed as events which are up defining the SV moving from lower than the threshold to higher than the threshold and down vice versa as presented in Figure 5.4.

5.5.1 Predictive analysis

In this work, we track each object by using the recurrent neural network (RNN) in different timestamps. Traditional artificial neural network assumes that the inputs/outputs are independent of each other. Such assumptions might be impractical in our case since we need to know the previous locations of a particular object if we want to characterize its movement and predict the future locations.

5.5.1.1 Motion modeling using LSTM

RNN considers inputs/outputs as sequential information and executes various actions such that the output of the current action is dependent on the previous actions. The RNN, in our work, uses the history of locations for tracking an object. Instead of using binary classification which is commonly used in deep learning based tracking methods, we use regression for direct prediction of the locations which are being tracked.

We concatenate the locations of the detected objects from the RTS and then predict the location of each object which is being tracked for the next timestamp. Long Short-Term Memory (LSTM) is one of the common types of RNN which is used in a variety of applications. While traditional RNN repeats the modules following a common structure like using one tanh function, LSTM provides different structures for the repeating modules. LSTM delivers four components which include a cell, an input gate, an output gate and a forget gate [51] which is useful for our purpose. The cell stores the values and the gates use different activation functions.

Although LSTM shares the same architecture as RNN, the function for computing the hidden state is different. LSTM captures the input and output information which has been calculated so far. Consider O_b.Location is the location input at timestamp t_i. Input O_b.Location can be considered as a one-hot vector representing to the $i-1^{th}$ location of the object. Our goal is to predict next p locations such that $p \in \mathbb{N}^+$. Therefore, LSTM will be unrolled into a neural network of n layers. The first hidden state is usually initialized to zeroes. Let, h_i be the hidden state at timestamp t_i. The cell in h_i can be considered as the memory of the network where it is calculated based on the previous hidden states and inputs along with the current input which can be given as [52],

$$\overline{C_i} = \tanh(W_C.[h_{i-1}, O_b] + b_C) \tag{5.6}$$

$$C_i = I_k * C_{i-1} + j_i * \overline{C_i} \tag{5.7}$$

The output θ_i is based on the cell state which runs through a sigmoid layer followed by a tanh that gets multiplied by the sigmoid gate's output. Output θ_i can be given as,

$$\theta_i = \sigma(W_\theta.[h_{i-1}, O_b] + b_\theta) \tag{5.8}$$

$$h_i = \theta_i * \tanh(C_i) \tag{5.9}$$

For each situation, the situation-aware RTS identifies next predicted p locations to the considered RTS and other objects in its environment. We use the predicted locations of the environmental objects to detect the possibility of collision.

5.6 Discussion

We analyze the knowledge-base to determine the probability of failure in different environmental situations by performing a fault-tree analysis. We also conduct a performance analysis by identifying the capacity along with the usage of the RTS at different time intervals. The probability of failure in a particular situation can be used to determine whether the RTS is operating in the expected mode or not. The validation framework also provides reliability by defining a verification action which allows the RTS to change its operating modes at runtime. The RTS can satisfy the user-defined safety and performance constraints and avoid failure in adverse environmental situations by switching its operating mode at runtime.

Chapter 6

Experimental analysis

6.1 Introduction

Uncertainties in the environmental situations of the RTS impose challenges on predicting the runtime behavior and ensuring adaptations within a predefined response time during system design. An RTS customarily executes a number of concurrent tasks sharing the processors [1]. Guaranteeing functional and timing behavior for a particular situation requires the identification and characterization of the adaptation requirements. Hence, it is essential for the RTS task model to allow a description of the resource requirements of the adaptive tasks. It is also necessary to guarantee the feasibility of the adaptive tasks before including them in the task model. Our goal in this thesis is to the monitor environment of the RTS, characterize the environmental situations, identify the adaptive tasks needed to be activated in each situation, and construct a SATM which allows the RTS to execute a set of uniprocessor feasible adaptive tasks.

6.2 Objectives of the experimental analysis

We conduct a number of experiments to illustrate the applicability of the proposed situation-aware RTS. One of the main objectives of the experiment analysis is to demonstrate how the adaptive tasks identified by the situation-aware RTS can be included and executed using existing task models. In addition, we present a novel graph-based task model called SATM and show that the proposed SATM provides an improvement in terms of metrics which include scheduling overload, average adaptation time, average response time and the total number of adaptation failures with respect to the existing task models.

Therefore, we divide this chapter into different sections:

Section 6.4 presents the experimental results associated with operational environment modeling which include three subsections: Real-time object identification and classification, identification of events along with their real-time and non real-time properties and formation of the knowledge-base.

Section 6.5 presents the experimental results associated with the proposed situation-aware graph-based task model. Which include subsections such as comparative analysis of the resource demands of the adaptive tasks in different case studies, evaluation of timing constraint and graph-based properties, characteristics of generated SATM and comparative analysis of SATM with existing task models.

Section 6.6 focuses on satisfying user-defined constraints which include subsections such as, identifying the safety constraint, identifying the performance constraint, validation framework and the predictive analysis.

To the best of our knowledge, a comparative framework to analyze the improvements of our proposed scheme is absent. This is mainly due to the formation of SATM by characterizing the environmental situation, uniquely identifying the adaptive tasks in each situation, and including the adaptive tasks associated with the environmental situation to SATM based on some predefined timing and graph-based constraints.

6.3 Experimental case studies

We demonstrate the usability and applicability of our experimental goals using three case studies: an automotive RTS, a real-time traffic monitoring system and a UAV flight control system. Each Case-study is executed in two different scenarios to eliminate the biasness of the experimental results that can be achieved using a particular scenario. Moreover, these case studies include RTS that are in motion (Case-study 1 and 3) or static (Case-study 2).

Case-study 1. **Automotive RTS:** We obtain the environmental input stream from an automotive real-time system which is being driven in Warsaw, Poland [53]. We use the input stream provided by the sensor to characterize various situations of the system and form a SATM.

Case-study 2. **Real-time traffic monitoring system:** We monitor the environment of a real-time traffic signal [45] which contains movements of various vehicles and pedestrians along with changes in traffic signals in Jackson Hole Town Square, Jackson, USA.

The system interacts with various objects of its environment and generates a SATM which allows the system to execute additional tasks at runtime.

Case-study 3. **UAV flight control system:** We also obtain the environmetal input stream of the environment of an UAV which is running in Brigham City [54] (Scenario 1) and New York city [55] (Scenario 2). The environment of the UAV contains movements of various objects (such as people, car, and truck) as well as obstacles (like high rise buildings, and trees) in its path.

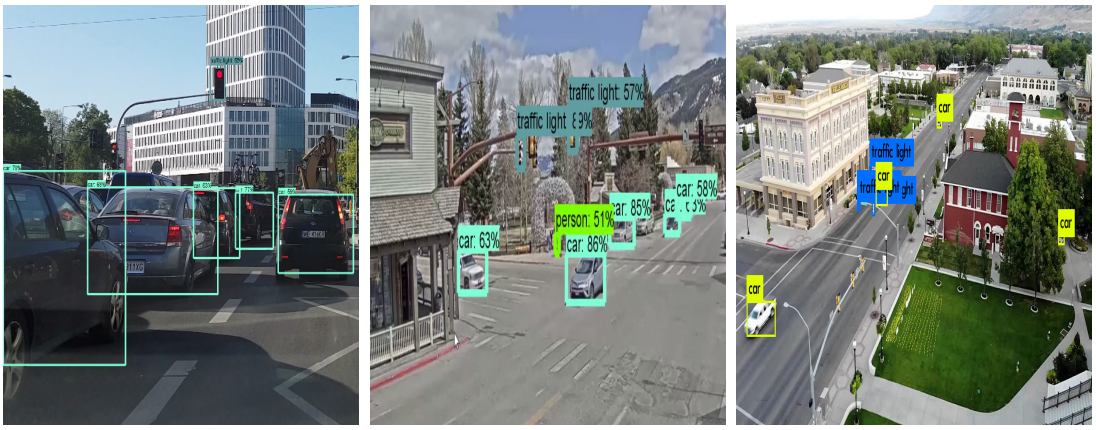
6.4 Operational environment model

A dataset of an RTS can allow us to analyze the characteristics of system behavior along with its users and the environment. Although many data collection approaches exist, storing video stream is more useful as it provides sequential real-time information of the system and visually represents the data so that we have a clear, straightforward and precise understanding of the execution environment. Hence, we receive video stream as input.

The object detector and classifier in the detection module of the operational environment model views object detection in a video frame as a regression problem. Identification and classification of the object from a video frame are complicated. Most of the early works focus on identifying the object using feature extraction approaches which include Haar-like features, Histogram of oriented gradients, Scale-invariant feature transform, Speeded up robust feature and classifying using different machine learning algorithms like Support vector machine [56], Random forest [57], and Artificial neural network [58]. However, the deep neural network has gained much attention in recent days as it provides a significant improvement over the early approaches in terms of detection and classification accuracy.

6.4.1 Real-time object identification and detection

To detect and classify objects from the video stream received from the camera, we use a nine-layer convolutional neural network which is followed by two fully connected layers. We divide each video frame into 10×10 grid. The neural network detects an object by predicting its appearance in multiple boxes. It also identifies the class probabilities for each detected objects. We use the ImageNet dataset [59] to train our model offline, and PASCAL VOC [60] to evaluate our detection scheme. Object detection and classification using our scheme for the Automotive RTS (Case-study 1), Real-time traffic monitoring



(a) Automotive RTS (b) Real-time traffic monitoring system (c) UAV flight control system

FIGURE 6.1: Real-time object identification and classification using our approach

system (Case-study 2) and UAV flight control system (Case-study 3) are illustrated in Figure 6.1.

6.4.2 Identification of events along with their real-time and non-real time properties

Operational environment modeling includes analyzing the video stream and identifying the events in different situations of RTS. We also analyze the detected events and identify their real-time properties such as duration and periodicity and non real-time properties such as location and speed. We use the periodic property of the events to classify the events into periodic and aperiodic. The operational environment model characterizes environmental situations in terms of events identified in different timestamps. The statistics of the detected events in the two scenarios of Case-study 1, 2 and 3 are presented in Table 6.1.

In Table 6.1, C denotes Case-study, and S denotes Scenario. For example, C1-S1 represents Case-study 1 - Scenario 1. For each scenario, for Case-study 1, 2, and 3, Table 6.1 illustrates the total number of identified events. Table 6.1 also shows the number of basic and derived events in each scenario as well as compares the number of events in terms of static and in motion. For Case-study 1 - scenario 1, we find 98.6% events are basic, and 1.4% events are derived whereas for scenario two 98.02% events are basic. For Case-study 2, the percentage of basic events are 83.64% and 84.02% in scenario 1 and 2. Whereas, for Case-study 2 the ratio of basic-derived events are (5.11 : 1) and (5.26 : 1) in scenario 1 and 2 respectively.

TABLE 6.1: Statistics of the detected events.

	Events	Basic - Derived	Motion - Static
C1-S1	17234	16993-241	16765-469
C1-S2	9404	9223-181	9089-315
C2-S1	8113	6786-1327	6385-1728
C2-S2	9007	7568-1439	7114-1893
C3-S1	8221	5448-2733	6993-1228
C3-S2	9807	8068-1739	7614-2093

6.4.3 Formation of a knowledge-base

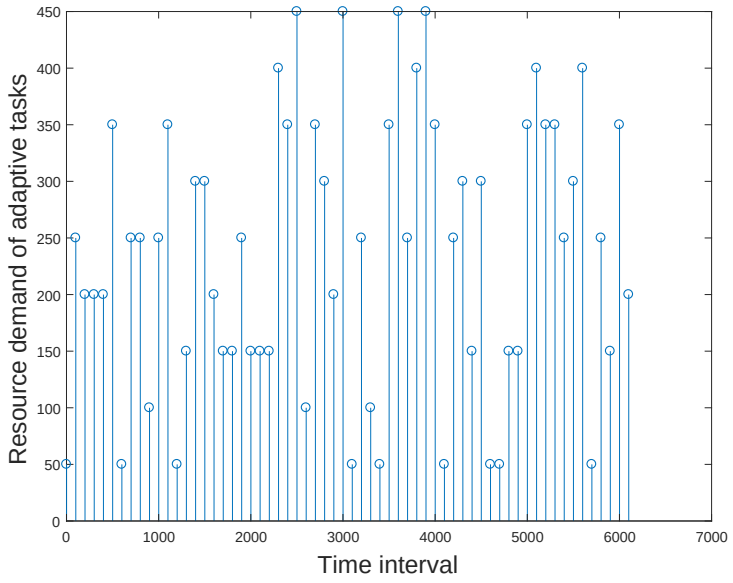
For each set of detected events, we use association rules to identify derived events which are the result of basic events. We perform event reduction where the occurrence of each event is recorded only once. For example, consider that E_1 is a basic event, it can also be used to form a derived event E_8 which is a combination of E_1 and E_2. We ensure that E_1 is recorded only once. Therefore, for each time video frame is obtained, we store each events id, timestamp, location, state, and speed. We form a knowledge-base which takes significantly less memory consumption than raw video stream data.
The initial sizes of the video streams received from Case-study 1 are 11917513 kilobytes (scenario 1), and 8550321 kilobytes (scenario 2), from Case-study 2 are 8691678 kilobytes (scenario 1) and 9511215 kilobytes (scenario 2) and from Case-study 3 are 14319678 kilobytes (scenario 1) and 11815432 kilobytes (scenario 1). The produced knowledge-base consumes significantly less memory in comparison to traditional video compression techniques. The sizes of the created textual knowledge-base are 2262, 1576, 1577, 1679, 2821, and 1878 kilobytes memory respectively for Case-study 1, 2 and 3.

6.5 The proposed situation-aware graph-based task model

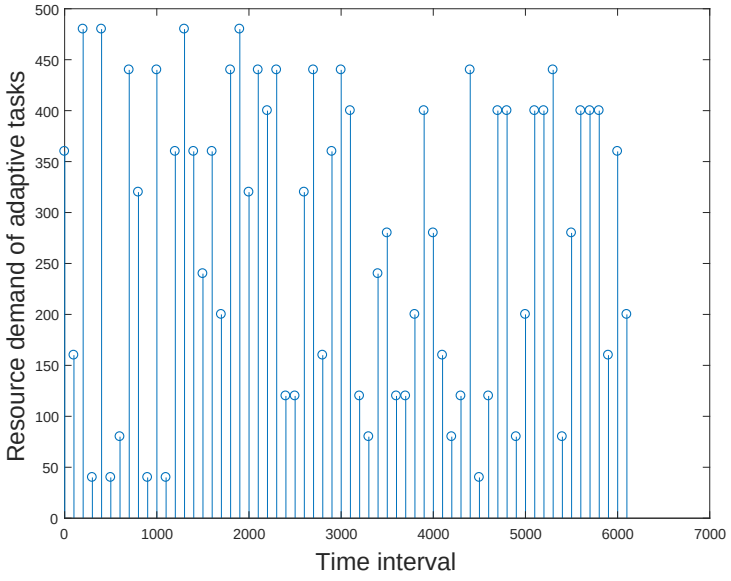
For each situation, we identify the adaptive tasks which are needed to be activated. The adaptive tasks considered in this work for different Case-study are illustrated in Table 6.2.

6.5.1 Comparative analysis of the resource demands of the adaptive tasks in different case studies

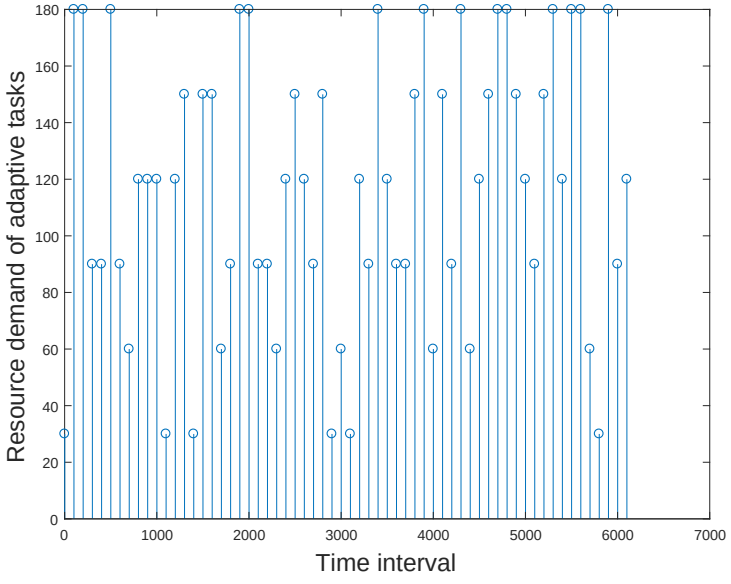
For each Case-study, in each situation, we map the detected events into the adaptive tasks defined in Table 6.2. Algorithm 5 evaluates the constraints associated with the activated tasks and determines feasibility. For each situation, if the execution path



(a) Case-study 1



(b) Case-study 2



(c) Case-study 3

FIGURE 6.2: Comparative analysis of resource demands in different case studies

TABLE 6.2: List of adaptive tasks considered in this work in different case studies

Case-study 1	Case-study 3	Case-study 2
Turn right - 90 degree	X + 30 degree	Turn red light- on
Turn right - 60 degree	X - 30 degree	Turn red light- off
Turn right - 30 degrees	Y + 30 degree	Turn yellow light- on
Turn left - 90 degree	Y - 30 degree	Turn yellow light- off
Turn left - 60 degree	Z + 30 degree	Turn green light- on
Turn left - 30 degree	Z - 30 degree	Turn green light- off
Speed up	Speed up	
Speed down	Speed down	
Brake	Brake	

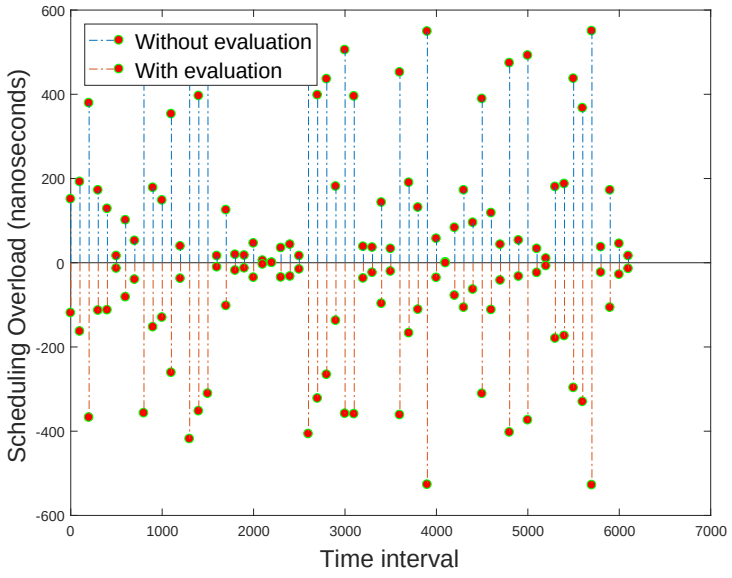
of the activated adaptive tasks is already included in the SATM, we avoid adding or merging the tasks in SATM. However, if the adaptive tasks are absent in the SATM, Algorithm 5 identifies the execution path and adds or merges them with existing SATM offline. Figure 6.2 illustrates the resource demands associated with the adaptive tasks identified in each situation for all three case studies.

6.5.2 Evaluation of timing constraint and graph-based properties

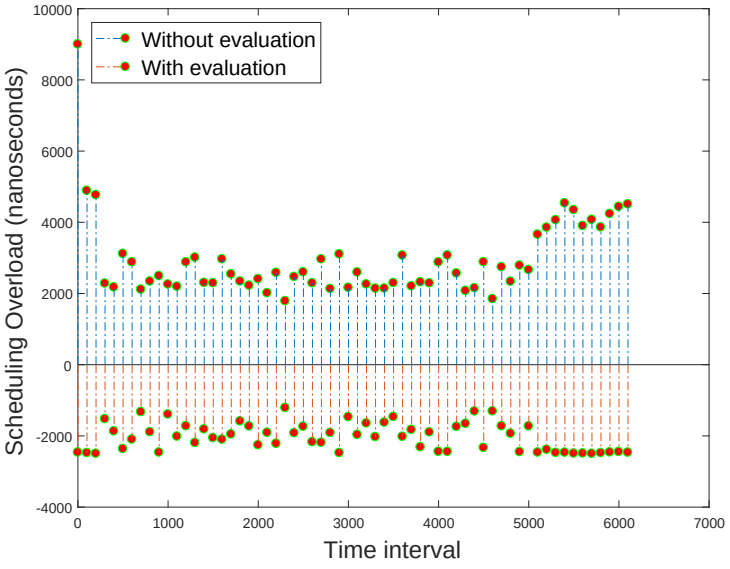
For each situation, the proposed RTS evaluates the identified adaptive tasks using a number of constraints. It avoids including the adaptive tasks which violate the timing and graph-based constraints to the SATM.

6.5.2.1 Comparison of scheduling overhead with vs. without timing evaluation

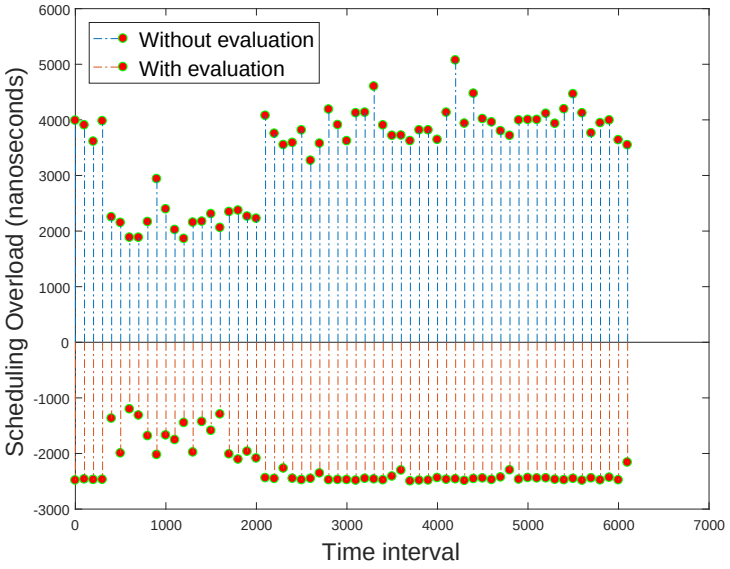
We perform a comparison of the scheduling overhead (in nanoseconds) associated with the adaptive tasks obtained in different situations for all three case studies considering and without considering timing evaluations. With the introduction of the timing evaluations at runtime, we experience reduced resource demands which can be translated to decreased scheduling overhead in different situations because the proposed RTS avoids including those tasks which do not satisfy the constraints. Figure 6.3 illustrates that the scheduling overhead for the adaptive tasks are always either equal or low when we consider timing evaluations.



(a) Case-study 1



(b) Case-study 2



(c) Case-study 3

FIGURE 6.3: Comparative analysis of the scheduling overload using vs. without using timing evaluations

6.5.2.2 Comparison of the probability of failure with vs. without timing evaluation

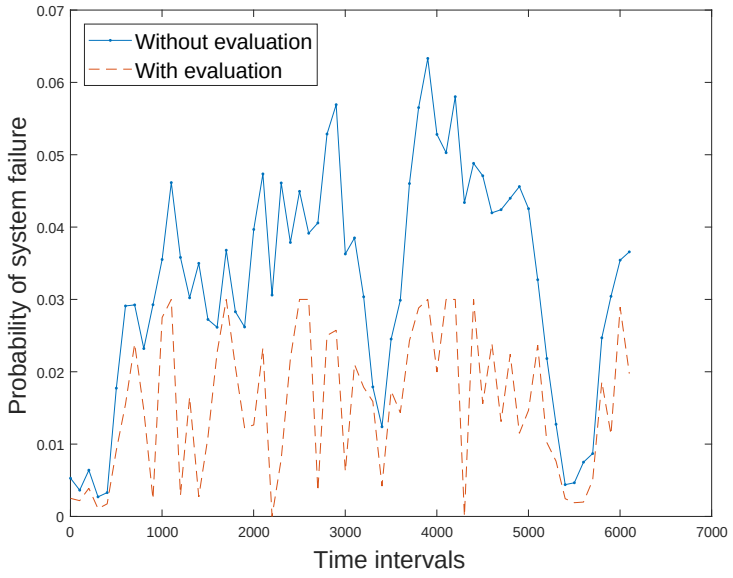
Each adaptive task associated with an environmental event generated various external components (objects). Different components have different failure rates. In this case, we consider the causal failure probabilities associated with the components which are generating the tasks. For the same data and the same system, we verify the tasks associated with an event. Our system rejects the tasks associated with the event or component whose failure probability is high. We determine the failure probability of the system again, and Figure 6.4 illustrates the probability of system failure without and considering the evaluations. Figure 6.4 demonstrates that the probability of failure is much lower when the evaluations are performed (for Case-study 1, 2 and 3).

6.5.2.3 Comparison of self-adaptation time with vs. without timing evaluation

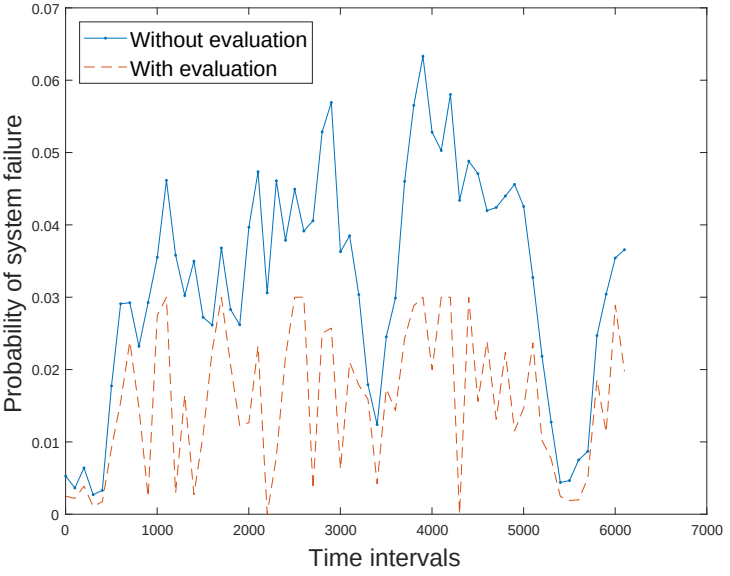
For each situation, the system evaluates the identified adaptive tasks using a number of timing TC and graph-based constraints GC. It avoids including the adaptive tasks which violate the timing and the graph-based constraints to the SATM. We perform a comparison of the resource demand(in nanoseconds) obtained at runtime for both case studies using and without using TC and GC. With the introduction of the TC and GC at runtime, Figure 6.5 presents a significant improvement in the resource demand because the RTS avoids including those tasks which do not satisfy the timing and graph-based constraints.

6.5.3 Comparative analysis of SATM with existing task models

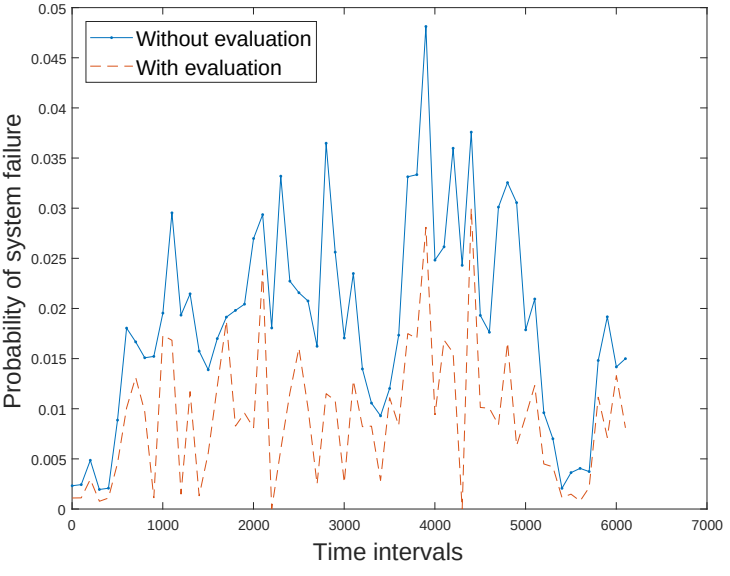
For all the adaptive tasks obtained in different situations of Case study 1, 2 and 3, we use existing multiframe task models such as GMF and NC - GMF and graph-based task models such as RB, RRT, and NC - RRT and schedule them in a uniprocessor environment. For each situation, for each task model, we identify the average execution time of the adaptive tasks (average adaptation time). We also identify the overall average response time where we consider both internal and adaptive tasks. An adaptive task set exhibit adaptation failure if they can not satisfy the timing evaluations. For each model, in each Case-study, we also identify adaptation failures.



(a) Case-study 1

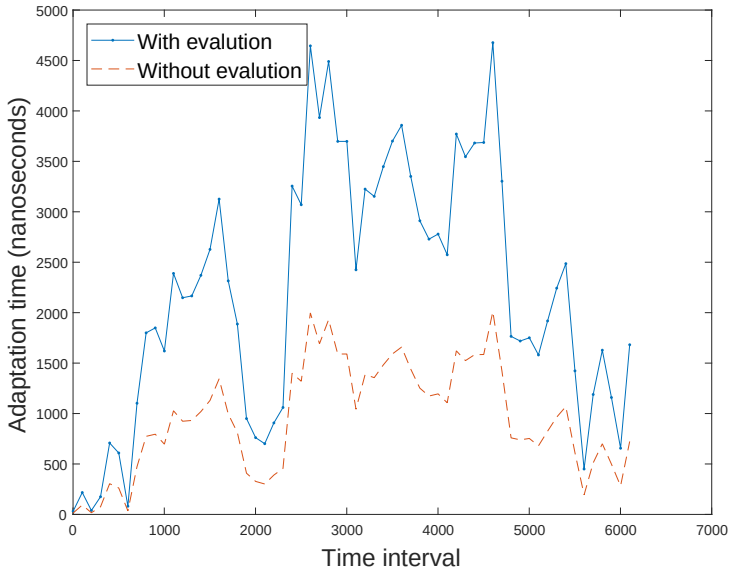


(b) Case-study 2

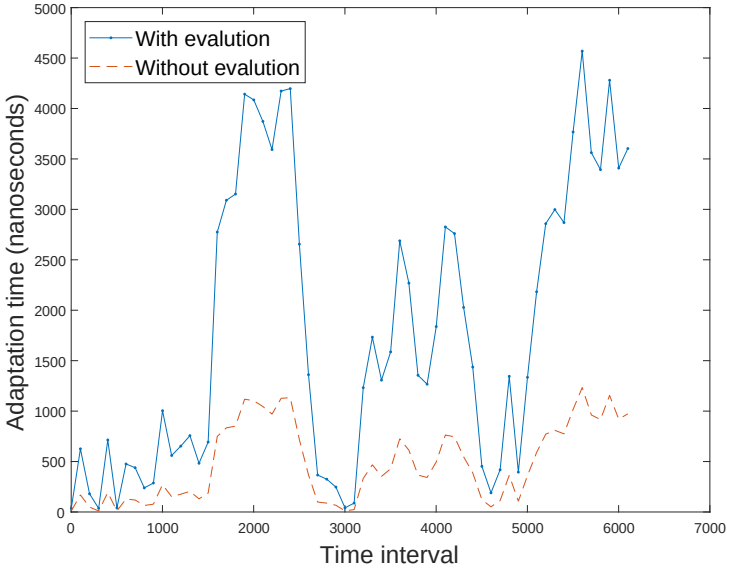


(c) Case-study 3

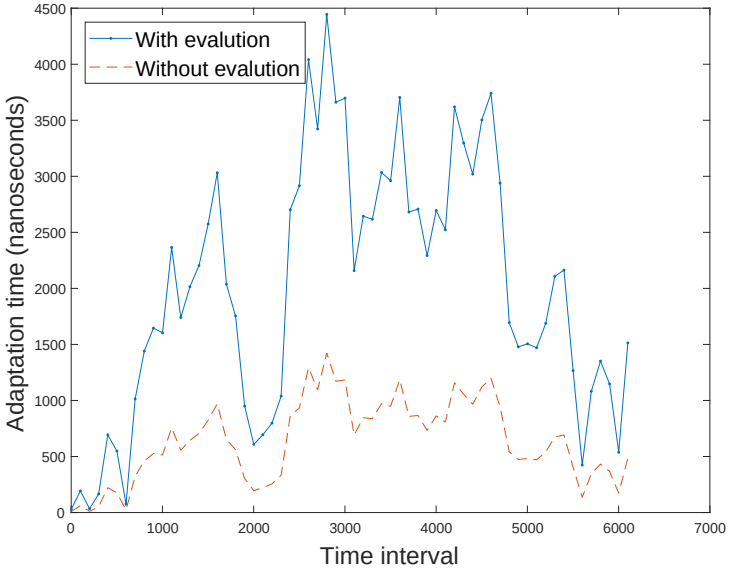
FIGURE 6.4: A comparison of probability of failure (with vs without evaluation)



(a) Case-study 1



(b) Case-study 2



(c) Case-study 3

FIGURE 6.5: Improvement of adaptation timing and graph-based evaluation.

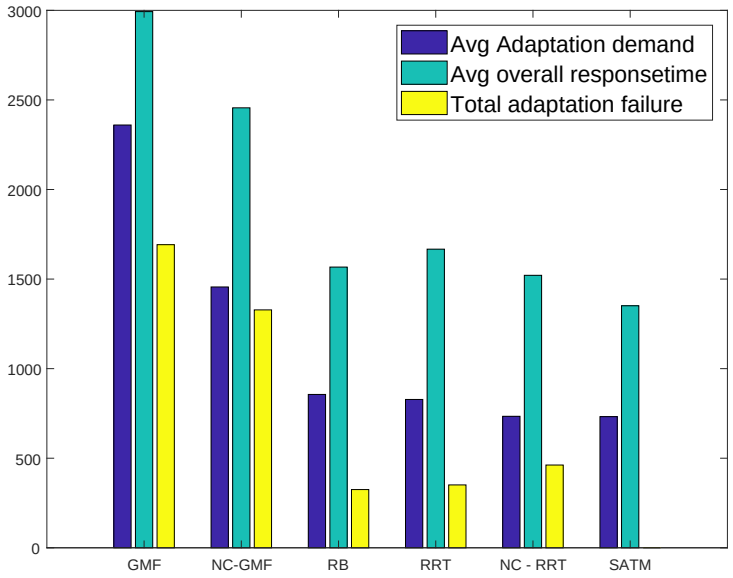
While identifying the adaptive tasks associated with a particular situation, the proposed SATM efficiently maps events with tasks. For each event, we identify whether the task associated with the event is already included in the SATM or not. If the task is already present in SATM, we avoid including (and thereby executing) it in SATM. Hence, for multiple events (which exhibit the same occurrence pattern), we add just one task. Moreover, SATM also has a provision for merging the tasks with existing paths such that the overall response time is lower. Hence, for a particular situation, the length of the execution path of the adaptive tasks provided by SATM (adaptation time) is significantly less in comparison to the existing task models.

We perform a comparison of scheduler complexity using and without using SATM. Figure 6.6(a), Figure 6.6(b), and Figure 6.6(c) represent a comparative analysis of the task models which include GMF, NC-GMF, RB, RRT, and NC-RRT with the SATM. With the introduction of the SATM, we see a significant improvement in average adaptation time, average response time due to reduced length of the considered execution path of the adaptive tasks. Also, execution paths which have reduced length are more likely to satisfy time timing evaluations. Hence, in Figure 6.6, we also experience fewer adaptation failures in all case studies. In this work, we consider the time interval δ as 2500 nanoseconds. Therefore, for each time interval, $\delta = 2500$ is considered as the maximum supply.

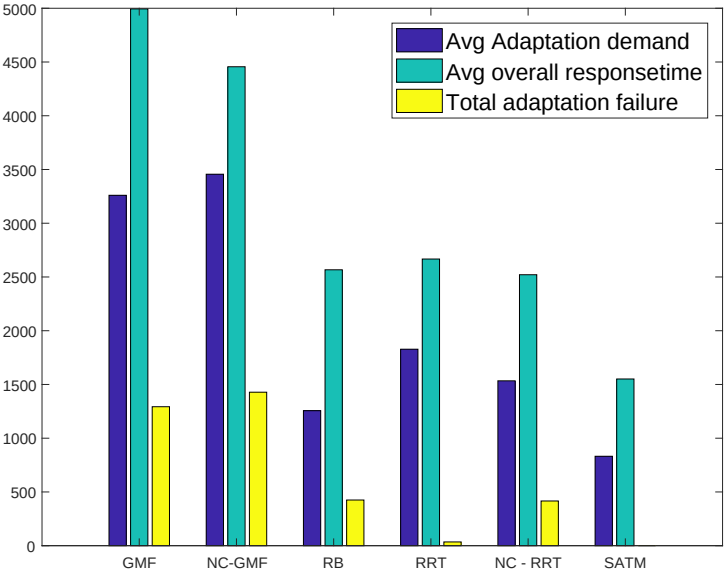
Lemma 1 and 2 imply that our system can handle overload situations because the length of the execution path (even during merging with an existing path) never exceeds δ. Figure 6.2 also validates this statement because of the presence of SATM, the proposed RTS ensures that the resource demand never exceeds 2500 nanoseconds (maximum supply) in any time interval. Since the resource demand can exceed the supply 2500 nanoseconds, the experimental results also show that the proposed SATM is feasible.

6.5.4 Characteristics of generated SATM

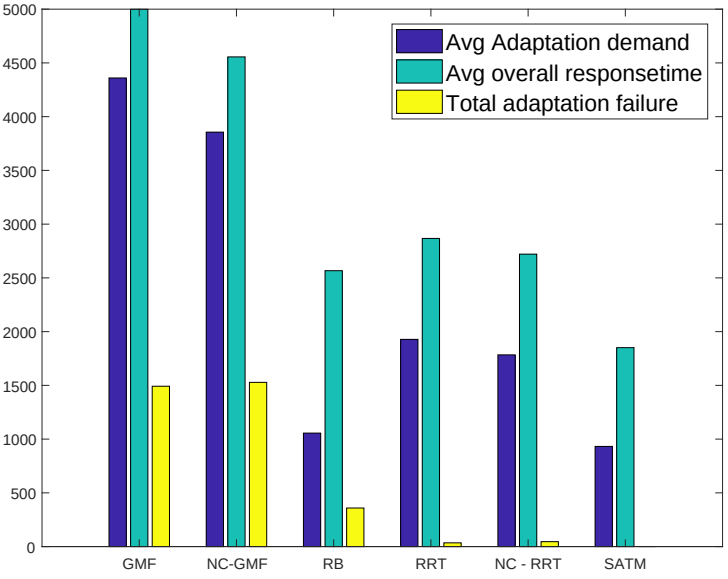
In this work, we use historical and current events from the situation-driven dataset to characterize the runtime behavior of the RTS at different time intervals. For each time interval, we identify the adaptive tasks that are needed to be executed due to the events obtained from the environment. We determine the overload of the system based on the set of available tasks which need to be executed. We also calculate the response time



(a) Case-study 1



(b) Case-study 2



(c) Case-study 3

FIGURE 6.6: Performance comparison of different task models with SATM

and execute available tasks such that a particular task is not executed more than once. Hence, unnecessary execution of a task more than once is removed.

TABLE 6.3: Characteristics of the SATM.

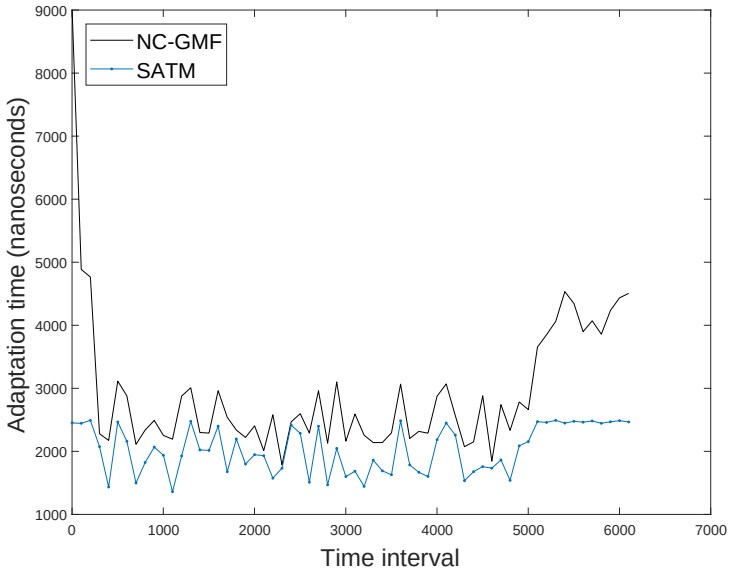
	Total Events	Number of vertices	Number of edges
C1-S1	17234	9	44
C1-S2	9404	9	43
C2-S1	8113	9	56
C2-S2	9007	9	68
C3-S1	8221	6	36
C3-S2	9807	6	36

We use the SATM to execute the tasks at runtime if they are already included in the SATM. Otherwise, we store their information and further evaluate the constraints and update the SATM (offline), if they satisfy the constraints.

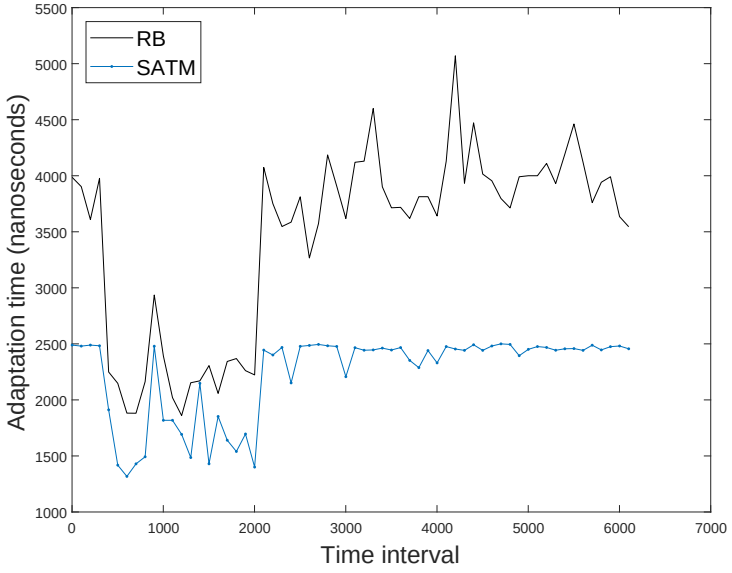
Table 6.3 shows that for Case-study 1 - scenario 1, the generated SATM contains nine verities (tasks) and 44 edges. Whereas, for scenario 2, the SATM consists of nine vertices and 43 edges. For Case-study 2, the constructed SATM has nine vertices as well as 56 edges for scenario 1 and nine vertices along with 36 edges for scenario 2. The reason behind the generated SATM containing a smaller number of vertices is due to the efficient mapping of multiple events to a particular task and merging the tasks in an existing execution path. In the future situations, we obtain same/similar (events which have same occurrence pattern) events and thereby, similar situations for a number of times at runtime. Table 6.3 illustrates that the proposed can represent the execution behavior of the adaptive tasks of the RTS in smaller memory.

6.5.5 Comparative analysis of the adaptation time (SATM vs. existing task models)

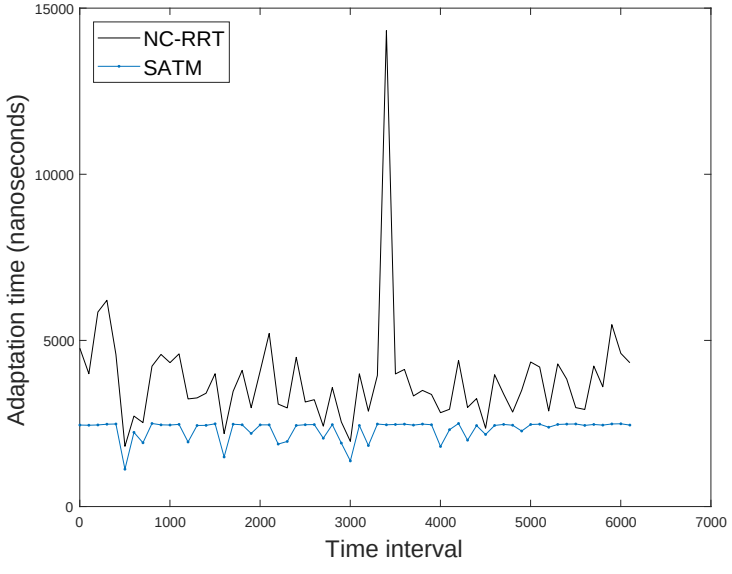
In this work, for a particular situation, the RTS can use a pre-determined execution path, if the situation has appeared before. Figure 6.7 illustrates that cases in which the tasks associated with the identified events in a particular situation are already present in the SATM, we experience a significant reduction in adaptation time for identification of the execution order of the adaptive tasks. The reason for such reduction is that the execution of a number of activities which include evaluation of the constraints, identifying the execution orders, finding vertices, merging the vertices associated with the adaptations with existing execution paths does not take place in these cases, because the vertices associated with the situation is already included in the SATM.



(a) Case-study 1



(b) Case-study 2



(c) Case-study 3

FIGURE 6.7: Improvement of adaptation time due to SATM at runtime.

6.6 Satisfying user-defined constraints

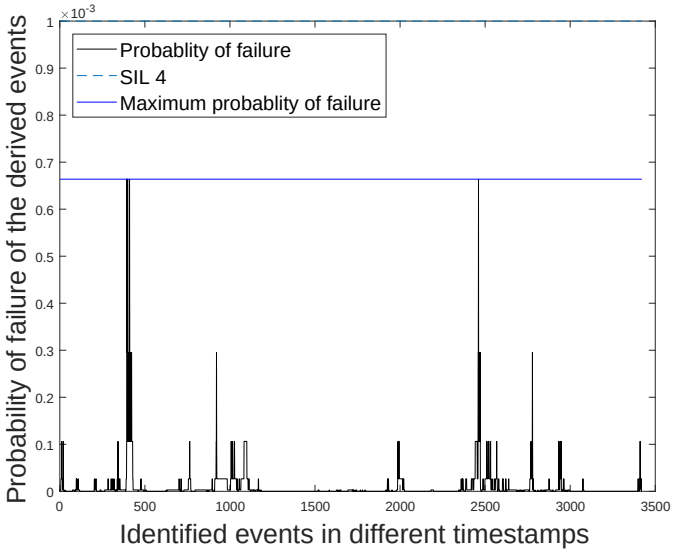
6.6.1 Identifying the safety constraint

We use fault tree to perform deductive failure analysis of the RTS. Fault tree analysis also allows us to have meaningful insights on identifying key system elements, environmental events which can cause a failure and investigates many ways a fault can occur. Our system performs both component and event-based safety analysis. For component-based analysis, we use safety integrity level defining failure probability of different components of the system in various timestamps of video frame arrival. The fault tree deduces failure likelihood of the undesired top event (which in our case is an accident and it can be due to component failure or collision between two events that are in motion).

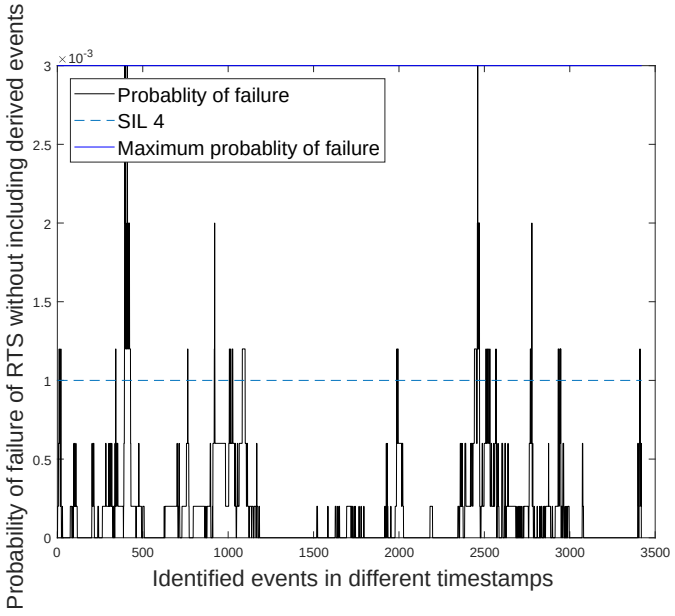
In each timestamp, we identify events that might lead to the top events and their associated probabilities. But this is the result obtained from only from the straightforward events (basic) which are already detected from the video streams. However, the system can experience some uncertain events which might go unnoticed in video streams. We use the Bayesian formula to determine the probability of the uncertain events from the detected events. Bayesian analysis enables us to take uncertainties related to the system environment into account and allows incorporating prior information. Figure 6.8 presents the probability of failure of the derived event, the probability of failure without considering the derived event and probability of failure of the system considering the derived event (safety constraint) for Case-study 1. Similarly, we identify the probability of failure for situation-aware RTS for Case-study 2 and Case-study 3.

6.6.2 Identifying the performance constraint

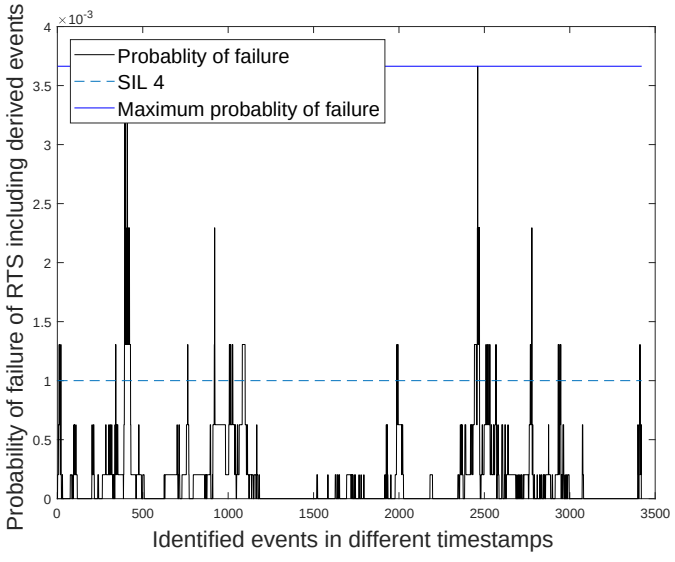
We use different time windows for identifying the performance of the RTS. For each time window, we identify the number of events processed. The maximum capacity of the system is calculated by comparing the maximum number of events detected in all the different time windows. Our system calculates maximum load and selects the time window which contains the maximum number of events being processed. For each time window, we identify the usage as the cumulative overhead of the time required for processing the events. Our performance analysis takes the entire time interval (starting from one to video frame arrival time) into account. As the system is introduced with more events in different scenarios, the system delivers a more accurate reflection of its capacity



(a) Probability of failure of derived events

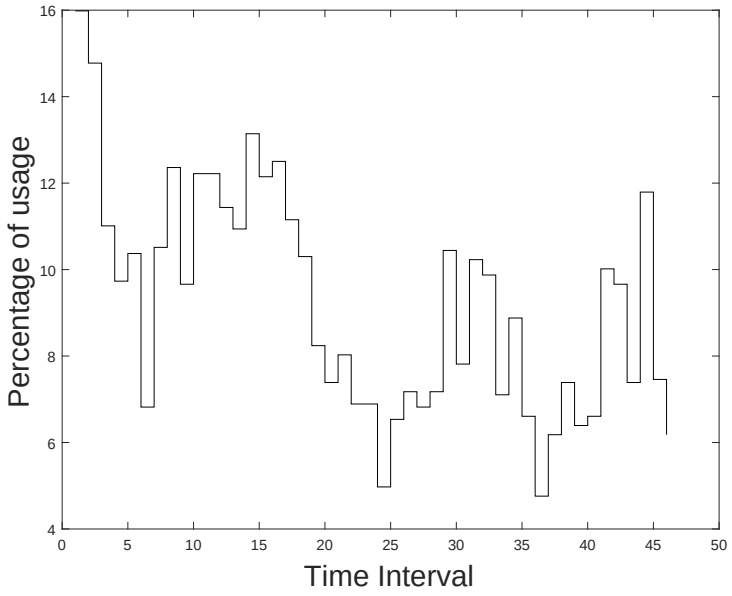


(b) Probability of failure without including derived events

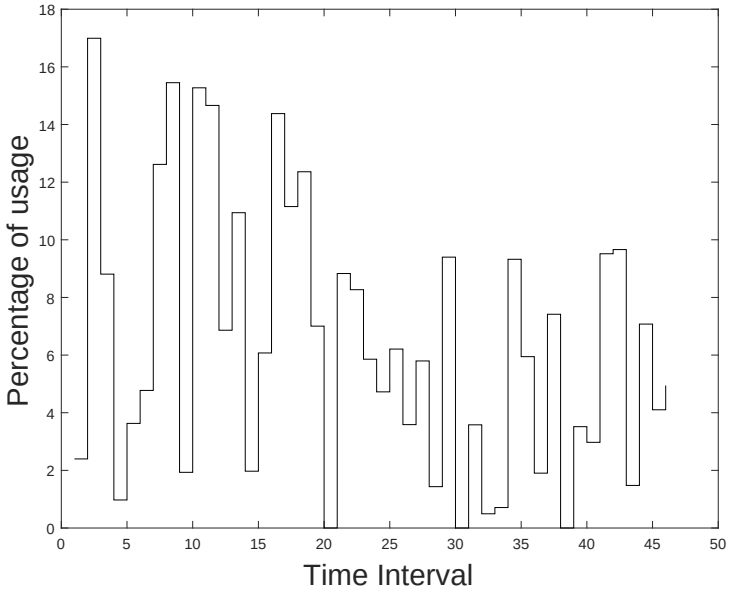


(c) Probability of failure of the situation-aware RTS

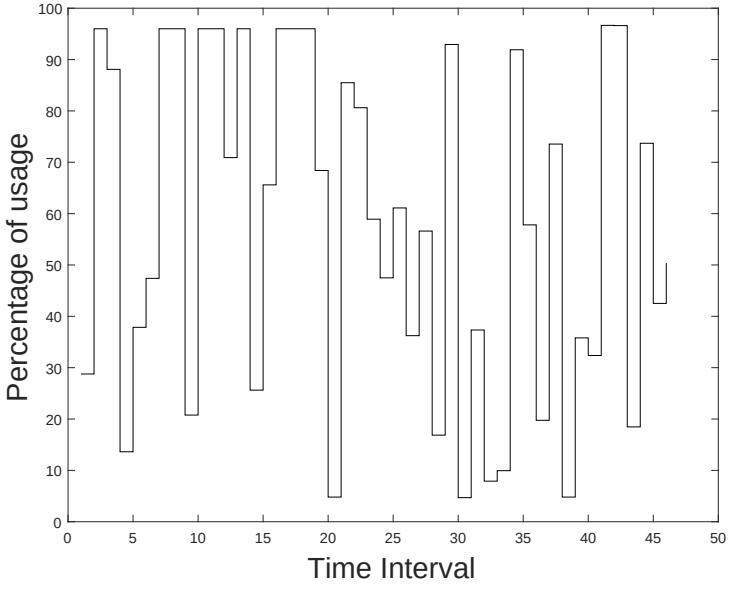
FIGURE 6.8: Probability of failure of the situation-aware RTS in different timestamps for Case-study 1



(a) Case-study 1



(b) Case-study 2



(c) Case-study 3

FIGURE 6.9: Percentage of usage due to detecting and processing events

usage. We can use performance analysis to provide some constructive feedback and suggestions which can help the system to improve its efficiency. In our experiment, a time interval of 55 milliseconds was selected as it contains a maximum of 183 detected events. We determine the percentage of usage for the selected time window. Figure 6.9(a), Figure 6.9(b), and Figure 6.9(c) illustrates the capacity usage of the system for Case-study 1, 2 and 3 respectively.

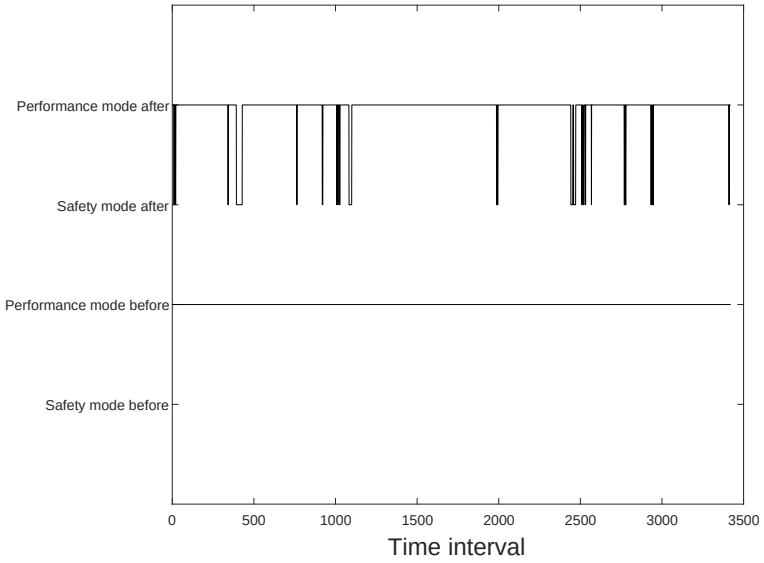
6.6.3 Validation framework

The RTS system presented in our work has two modes of operations: safety, and performance. For each time the validation framework calculates the probability of failure of the system using fault tree analysis. The validation framework defines a threshold value called SV which is the total probability of failure to determine whether a system is safe or not and determine the expected mode. The validation framework uses a state machine to demonstrate the system behavior where the system modes are represented by states and two events namely up and down are used for transition between the modes.

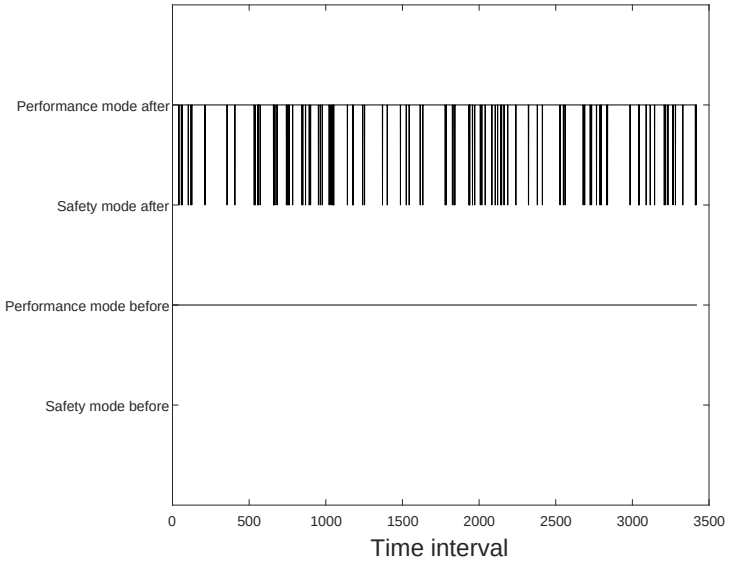
6.6.3.1 Comparative analysis of modes changes (with vs. without validation framework)

Our system satisfies the user-defined constraints by changing its operating mode at runtime. Situations in which the probability of failure is high, it assures reliability by changing the operating mode to Safety (from performance). Figure 6.4 demonstrates that the probability of failure is much lower when the validation framework is used. This is because when the validation framework is used the system changes its operating mode to safety when the probability of failure is higher than TH = .01 and satisfies user-defined constraints.

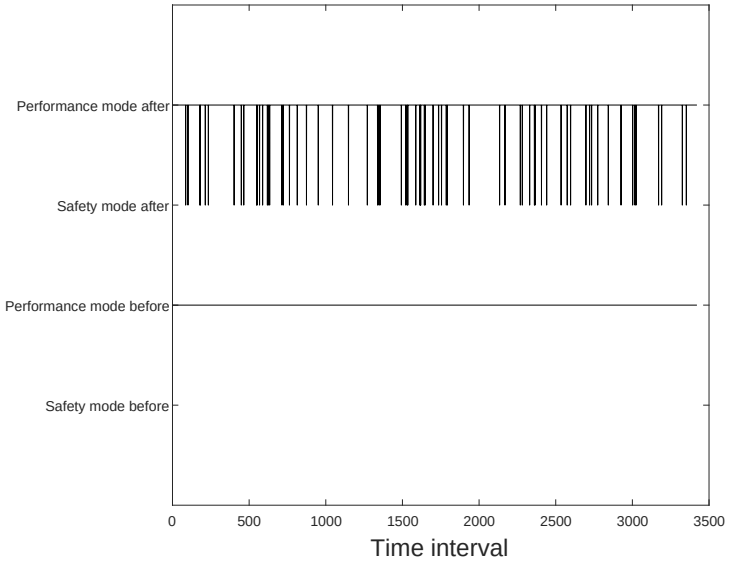
With the arrival of a new situation, in each time interval, we determine the expected mode. If the probability of failure is more than a predefined threshold value (which is .01), our expected mode safety. The system changes its operating mode at different times so that it can avoid any failures at runtime. Figure 6.10(a), Figure 6.10(b) and Figure 6.10(c) present changes in the operating mode at different time intervals (considering and without considering validation framework) for Case-study 1, 2 and 3 respectively.



(a) Case-study 1

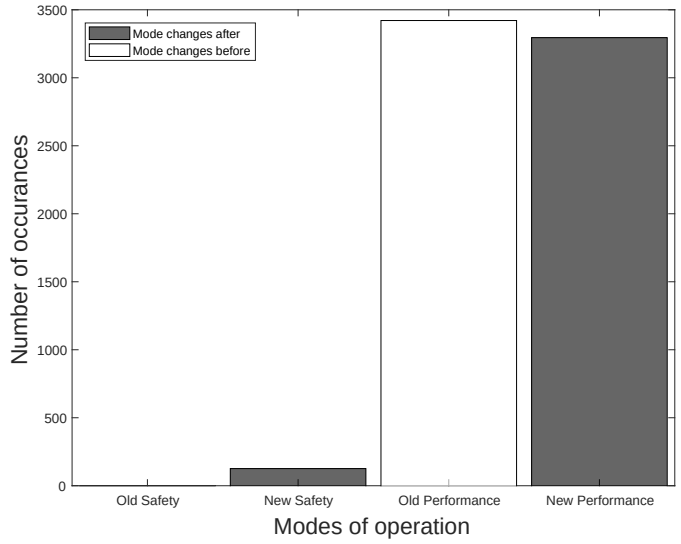


(b) Case-study 2

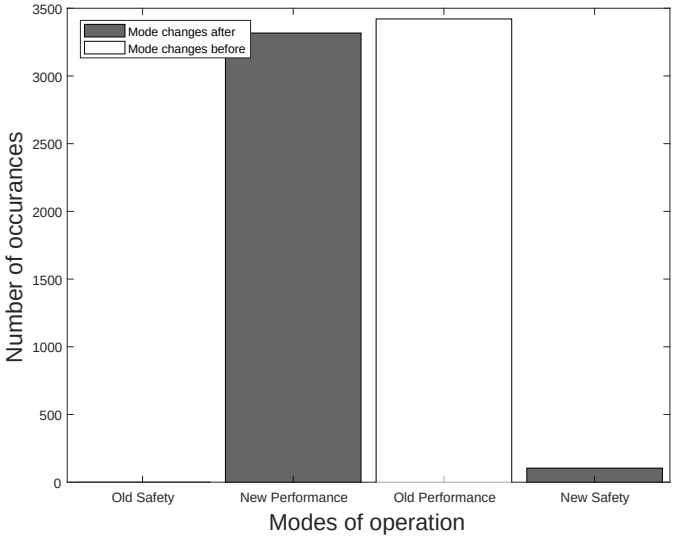


(c) Case-study 3

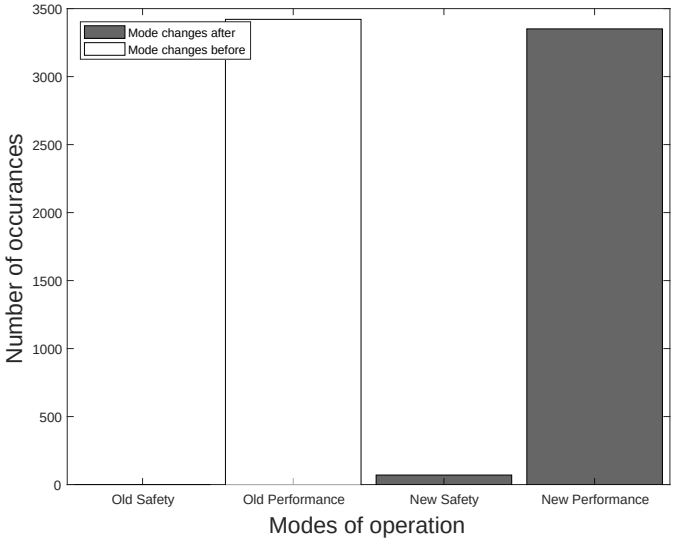
FIGURE 6.10: Changes of modes of operation in different time interval



(a) Case-study 1



(b) Case-study 2



(c) Case-study 3

FIGURE 6.11: A comparison of mode changes with vs. without validation framework

We also present the number of occurrences of various operating modes of the system. Figure 6.10(a), Figure 6.10(b) and Figure 6.10(c) demonstrates mode switching from safety to performance (and vice versa) as well as the total duration (time interval) in the destination mode. The system operates in performance mode in most of the time intervals to satisfy the performance (usage) requirements. It also switches from the performance to the safety mode when the probability of failure is high. This experimental result illustrates that the RTS meets our user-defined constraints satisfaction goal at runtime because the system can use multiple modes of operation at runtime to guarantee performance and safety requirements.

(a) Randomized detection of collision (b) Detection of collision using our approach

FIGURE 6.12: Prediction of collision using Motion modeling

Figure 6.11(a), Figure 6.11(b), and Figure 6.11(c) presents a comparative view of the occurrences of different modes in various time interval for Case-study 1, 2 and 3 respectively. The old result (mode changes) is obtained without considering the validation framework. Figure 6.11(a), Figure 6.11(b), and Figure 6.11(c) presents that, with the introduction of validation framework, the RTS operate more (in terms of time intervals) in safety mode and thereby satisfies the user-defined safety and performance constraints.

6.6.4 Predictive analysis

In this thesis, we perform trajectory predictions by performing real-time tracking of the identified events associated with objects. We keep track of all the events with their location along with an average change in their position. For each event in motion, our system determines average the changes in x and y coordinate of the objects. We use current location of the object along with its average changes and use LSTM to perform

motion modeling which predicts the future locations of all the events and identifies whether collision takes place within any two or more events.

Although some existing approaches prevail that detects collisions using various physical models. Our prediction model is adaptive and can address changing situations as it updates the location information each time a new frame arrives and recalculates the possible future locations. Our trajectory prediction framework is tested in different video streams, and it was successfully able to predict collisions. An illustration of comparison for detection of collision using our framework with a randomized collision prediction approach is provided in Figure 6.12.

Chapter 7

Conclusion

With the growing number of real-time systems and extensive integration of real-time systems in different Cyber-Physical Systems, Smart Cities and Internet of Things, users today expect systems to operate whenever and wherever they want. Systems are now becoming highly interactive, consist of several operating modes and must be able to execute in a changing environment. Designing, configuring, and assuring the functional and runtime behavior of such systems are very challenging. To cope with the challenge, we present the design of a situation-aware real-time system which can satisfy user-defined constraints.

We present a situation-aware graph-based task model which allows an RTS to accommodate the execution of adaptive tasks in different situations. To identify the adaptive tasks that need to be executed in a particular situation, we monitor the environment of an RTS and translate the events identified in a particular situation into a set of adaptive tasks. We ensure schedulability by defining a number of constraints and evaluating the adaptive tasks using the constraints. We avoid including the tasks to the tasks model which violate the constraints. Such evaluation allows the RTS to reduce resource demand of the adaptive tasks at runtime. Formation of SATM includes mapping the adaptive tasks as vertices and execution order between each pair of tasks as an edge. If the vertices satisfy the constraints, the proposed SATM finds their execution path and merges the new execution path with the existing SATM. SATM also facilitates a reduced adaptation time in different situations. Formation of SATM is performed offline. However, the SATM can handle a particular situation at runtime, if the vertices identified from the situation that are already included in the SATM.

The presented design of the situation-aware real-time system contains non-adaptive and

adaptive execution models. In non-adaptive execution model, the RTS only executes internal task set defined by current mode using the EDF scheduling algorithm. In adaptive execution model, the RTS monitors its environment, identifies the real-world occurrences as events and determines their real-time (such as duration, and periodicity) and non real-time (such as location, and speed) properties. We determine the association relationships involved among the events through performing association rule learning. We create a knowledge-base (offline) which stores the historical event information from the captured situations. The knowledge-base allows fast information retrieval in reduced memory and facilitates the formation of SATM.

We use the knowledge-base to determine the safety constraints in different environmental situations. Identification of the safety constraint involves performing a fault-tree analysis and determining the probability of failure of the RTS in each environmental situation. We also identify the performance constraint for each environmental situation by analyzing the capacity along with the usage of the RTS at different situation arrival time interval.

We present a validation framework, which uses the probability of failure identified in a particular situation to determine whether the RTS is operating in the expected mode or not. The validation framework also provides reliability by defining a verification action which allows the RTS to change its operating modes at runtime. The RTS can satisfy the user-defined constraints and avoid failure in adverse environmental situations by switching its operating mode at runtime. For example, the RTS can satisfy the safety constraint by operating in the safety mode when the probability of failure is high.

To the best of our knowledge, a framework for designing a situation-aware RTS that analyzes environmental input stream, identifies various events and extracting numerous real-time and non real-time properties among the events, discovers associations among the events, produces a knowledge-base, changes the modes of operation to ensure the user-defined constraints of the system at runtime, creates the SATM by characterizing the environmental situations, uniquely identifies the adaptive tasks in each situation, and includes the adaptive tasks associated with the environmental situation to SATM based on some predefined timing constraints and graph-based properties is absent.

The future work of this thesis includes enabling communications among the considered case studies. Moreover, we also aim to present additional user-defined constraints other than safety and performance. Another future work is to allow the system to operate in

additional operating modes (other than safety and performance) and implementing existing mode change protocols such as Maximum Period Offset, Minimum Offset without periodicity, Minimum Offset with periodicity, Asynchronous with periodicity and Asynchronous without periodicity for mode switching. Moreover, we also aim to formulate a task model which can characterize the mode transitions of all the considered modes. Moreover, we aim to execute the adaptive tasks using additional task models (other than GMF, NC-GMF, RB, RRT, and NC-RRT).

Modern RTS requires computing infrastructure which allows low-latency network connections with deterministic transmission time with other systems as well as the Internet. Fog computing has gained much attention in recent days where various analytics can be performed at end devices such as access points or set-top-boxes [61] which can be considered as fog nodes. An RTS embedded within fog architecture can allow processing to be performed to close as possible to the system. For example, consider a scenario where we have multiple vehicles running on a road (each having analytics endpoints), can send and process information in the fog node. Such RTS design can provide reduced network overhead and processing time as well as more security in comparison to storing and processing data using cloud computing.

We also aim to present a Fog-based analytics framework from mining the environmental input stream of the situation-aware system where we consider that the RTS has an analytics endpoint (fog node) which allows the system to communicate nearby transportation systems. For each situation, our goal is to send the events detected in a particular situation to the fog node and present a fog computing-based analytics framework which determines the user-defined constraints associated with each situation in the fog node.

Appendix A

An Appendix

Different symbols used in this paper can be listed as:

- $\mu = \{\mu_1, \mu_2\}$, is the set of RTS modes of operation.
- μ_{current} is the current operating mode such that $\mu_{\text{current}} \in \mu$.
- μ_{expected} is the expected operating mode such that $\mu_{\text{expected}} \in \mu$.
- $\tau_{\text{out}} = \{\tau_{\text{out}_1}, \tau_{\text{out}_2}, \ldots, \tau_{\text{out}_\text{r}}\}$ is a set of r adaptive real-time tasks such that $\text{r} \in \mathbb{N}^+$.
- τ_{MCR} is the task which triggers a mode change request. item τ_i is an active task defined as $\tau_\text{i} = (\alpha_\text{i}, \text{C}_\text{i}, \text{D}_\text{i})$, (such that $\text{i} \in \mathbb{N}^+$.) where,
  - α_i is the arrival time,
  - C_i is the worst-case execution time demand, and
  - D_i is the relative deadline of τ_i.
- $\tau_{\text{in}} = \{\tau_{\text{in}_1}, \tau_{\text{in}_2}, \ldots, \tau_{\text{in}_\text{q}}\}$ is a set of q active internal real-time tasks with $\text{q} \in \mathbb{N}^+$.
- P_i is the period of internal task $\tau_{\text{in}_\text{i}} \in \tau_{\text{in}}$.
- $\text{dbf}_{\tau_{\text{in}}}(\delta)$ is the demand-bound function for time interval δ and the set of tasks τ_{in}.
- $\text{rf}_{\tau_{\text{out}}}(\delta)$ is the request function for time interval δ and the set of tasks τ_{out}.
- O_b is the b^{th} Object such that $\text{b} \in \mathbb{N}^+$.
- E_c denotes c^{th} Event such that $\text{c} \in \mathbb{N}^+$.
- AR is the rule set defining association rules among the events.

- E_{basic} is the set of basic events.
- $E_{derived}$ is the set of derived events.
- $S_k = \{E_1, E_2, \ldots, E_d\}$ is the Situation identified at time t_k such that $k, d \in \mathbb{N}^+$.
- $F = \{f_1, f_2, \ldots, f_n\}$ is the set of n video frames taken at a time interval δ such that $n, \delta \in \mathbb{N}^+$.
- $ED = (x_1, x_2, \ldots, x_u)$ is a temporal vector which stores event information.
- KB is the generated knowledge-base.
- $G(S_k) = (V, H)$ is the situation aware task graph where,
  1. V is the set of vertices.
  2. H is the set of directed edges.
- $\theta(\tau_{in})$ is the worst-case estimated duration for the internal tasks.
- $T_{available}$ is the available free time slots after scheduling the internal tasks in δ.
- $TC_1(v_i), TC_2(v_i, v_{i+1}), TC_3(v_i), TC_4(v_i),$ and TC are the timing constraints.
- $\pi(S_k)$ is the execution path associated with S_k.
- $Length(\pi(S_k))$ is the length of the execution path $\pi(S_k)$ in terms of worst-case execution time.
- $dist(v_i, v_j)$ is the minimum distance of the vertex from $v_i \in V$ to $v_j \in V$.
- diam(G) is the maximum distance between the two vertices (in terms of execution time) of G.
- $GC_1, GC_2, GC_3,$ and GC are the graph-based constraints.
- SA_1 is the non adaptive scheduling algorithm such that $SA_1 = EDF$.
- SA_2 is the adaptive scheduling algorithm such that $SA_2 : \{\tau_{in} \cup (\tau_{out} \subseteq G)\} \rightarrow Pr$.

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