Definitions of Predictability for Cyber Physical Systems

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Abstract

With the recent proliferation of different types of Cyber Physical Systems (CPS), it is critically important to investigate the predictability of such systems. Along with functional correctness of the components, these systems must also ensure that timing and delay constraints of components are properly for the entire system to behave in a predictable manner in presence of various kinds of uncertainties. While the functional correctness of the CPS components has been investigated in the past, very little is available about the timing issues. The objective of this paper is to conduct an investigation of key issues involved to ensure the predictability of the system, introduce rigorous definitions of performance parameters, and propose metrics for their evaluation and analyze their suitability to be used in the presence of uncertainties in which CPS operate. The results are expected to provide greater insight into the time critical behavior of CPS components.

Keywords: Cyber Physical Systems, Predictability, I/O Behavior
Predictability, Time Predictability, Order Predictability

1. Introduction

Cyber-Physical Systems (CPS) are integrations of computation with physical processes. Embedded computers and networks monitor and control the physical processes, with feedback loops where physical processes affect computations and vice versa [38, 40]. Predictability is crucial for CPS testing and

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verification, which are required by time-critical applications such as traffic control, automotive safety, and health care systems [20, 38, 40, 41, 45]. To improve the predictability of concurrent and preemptive CPS, the first and foremost work is to figure out the properties that should be predictable in CPS and precisely define the concept of predictability.

The predictability problem resounds throughout the embedded systems community, particularly throughout the real-time community. Stankovic and Ramamritham discuss the need for predictability, with respect to the time requirements of different kinds of systems [52]. Thiele and Wilhelm define the time predictability by considering the difference between the real Worst-Case-Execution-Time (WCET) and the WCET bound, which is often called the pessimism of the analysis, as a measure for predictability [53]. Kirner and Puschner define predictability as the interval between the Best Case Execution Time (BCET) and the WCET, where a smaller interval means better predictability [28]. Grund et al. investigate and propose a template for the predictability definitions, and define the predictability as the quotient of the minimum execution time over the maximum execution time with all the possible inputs [21]. The state-of-the-art predictability definitions can be classified into four categories: 1) interval between BCET and WCET [28]; 2) quotient of BCET over WCET [21]; 3) quotient of WCET over WCET bound [53]; 4) quotient of BCET over WCET bound [53]. Almost all the aforementioned definitions of predictability are based on WCET and BCET, which are estimated by assuming the uninterrupted execution of a single task [4, 21, 28, 53, 56]. However, the assumption is not true for most of CPS due to the concurrent and preemptive nature of CPS [38]. In addition, CPS must be robust in presence of unexpected conditions, and adaptable to subsystem failures. Therefore, the predictability of CPS has more rigorous semantic requirements than the above definitions [40].

The objective of this paper is to investigate issues involved to ensure the time predictability of CPS, introduce rigorous definitions of performance parameters, and propose metrics for their evaluation and analyze their suitability to be used in the presence of uncertainties in which Cyber Physical Systems operate. Through analyzing the behaviors of I/O and function task of typical programming models and characteristics of CPS, we argue that both the function tasks and I/O must have time predictability and order predictability. The I/O behaviors must be predictable in terms of their ready time and the Inputs ready order, where the ready time refers to the interval between the time when the value in the I/O source changes and the time

when the value in the I/O port is modified correspondingly. The predictability of function tasks are discussed and defined according to the concurrent and preemptive characteristics of CPS. It includes the time predictability of individual task and tasks set. And the execution order predictability of tasks in a scheduling set must be predictable as well. We investigate the sources of uncertainties of different properties that must be predictable, and propose definitions for them based on the uncertainties and the template introduced in [21]. Table-1 shows the differences between the existing definitions and our definitions. The major contributions of our work are as follows:

- (1) We give a comprehensive catalog of possible unpredictability and summarize properties that must be predictable. We emphasize the importance of I/O predictability by analyzing their behaviors in different programming models, and we analyze the function task predictability requirements in the concurrent and preemptive environments.
- (2) A careful investigation of the uncertainty sources of different properties is made. By analyzing the major uncertainties, we propose metrics and formal predictability definitions for those properties. We present methods to calculate parameters that are used in the definitions.
- (3) To the best of our knowledge, this paper is the first to stress the importance of order predictability in addition to only time predictability reported in the literature. We propose new ideas to determine the order (i.e., the inputs ready order and the tasks execution order), and present methods to calculate their predictability.

Our definitions can serve as metrics for measuring and comparing the predictability of CPS. CPS that have greater predictability tend to have more reliable testing and verification results, as well as time safety. When applied during CPS design, the metrics help the designer in selecting suitable programming models, runtime systems and hardware platforms to satisfy safety as well as energy efficiency requirements. The order predictability can also help to improve the CPS design, i.e., a predictable inputs ready order is critical for the predictability of the input-determined real-time systems, and the task execution order is important to make the scheduling algorithm predictable and avoid some scheduling anomalies and the mutex hazards as well. Finally, since our predictability definitions capture major sources of uncertainties, they can be used to find out the bottleneck of the predictability. The designer can improve the system's predictability effectively by optimizing the bottleneck.

Table 1: A comparison between the existing predictability definitions and our definitions

	Existing Definitions	Our Definitions			
Behaviors	Function task	Function task		I/O	
Properties	Execution time	Response time	Execution Order	I/O Ready time	Inputs ready order
Sources of Uncertainties	Inputs, Hardware states	Inputs, Hardware states, Concurrency, Preemption, Scheduling, Runtime system, Mutex hazards		Sensor, Network, Memory delay	Inputs ready time, processing order
Metrics	Task execution time variability	Task response time variability	Execution order distance variability	Inputs ready time variability	Inputs buffer costs variability

The rest of this paper is organized as follows: Section 2 discusses the requirements of the predictability of CPS and summarizes the behaviors and properties that must to be predictable. We investigate the sources of uncertainties of each predictable property, and present formal definitions in Section 3. Section 4 shows the related works, and we conclude our work and show the future work in Section 5.

2. Predictability Requirements of CPS

In this section, we illustrate that both the function task behaviors and the I/O behaviors must be predictable by analyzing their logical and real time performance in different real-time programming models at first. Then, from the characteristics of CPS standpoint, we argue that both the time property and the order property of the different behaviors must be predictable.

According to Klein and Ralya [31], **Input** is defined as reading data from one or more sources of input; **Output** is defined as writing the results of the computation to one or more sinks, which may be devices and/or main memory; **function task** is defined as the process to compute output values, which are functions of the gathered input values. These definitions are used throughout this paper.

Figure 1: Logical abstraction and real time execution of different programming models

2.1. Behaviors Need to be Predictable

Most of the real-time programs are input-determined programs, i.e., if, for all sequences of input values and times, the program produces, in all runs, unique sequences of output values and times [29]. Therefore the I/O behaviors are critical to improve the predictability of the system. However, the I/O behaviors of most of the real-time programs are unpredictable in either the logical time (specified by programming models) or the real time (performed during run time). We use the example shown in Fig.1 to analyze the I/O behaviors of a task, which is realized in different programming models and executed in preemptive environments. The top half of Fig.1 shows the logical time of three real-time programming models (summarized in [16]). The bottom half shows the execution of a task in different real time periods, during which the task can be preempted by other tasks.

The *asynchronous model* bounds execution times using deadlines. A system built on the asynchronous model is a set of programs that consist of a finite number of tasks, which execute concurrently under the supervision of specific mechanisms such as real-time operating systems [16]. The execution of asynchronous program is correct if the tasks finish writing outputs before deadline. However, since no I/O behaviors are specified in the asynchronous model, the I/O behaviors are highly unpredictable in both the logical time and the real time. As shown in Fig.1 (a), the time to process I/O is not specified in the programming model. In the first real time period, the input and output happen at the 2nd time instant and the 7th time instant, respectively,

while in the second real time period, they are processed at the 1st time instant and the 8th time instant, respectively. In the *synchronous model*, the logical temporal reference is completely determined by the successive reactions of the system happening on the occurrences of observed events [8, 23]. Due to the synchronous assumption of the model, the I/O behavior is predictable in the logical time. In the real time, the input is processed at fixed time instant, such as PRET-C [2]. However, since the synchronous program is correct as long as the output completes before the next input, the output behavior is still not predictable in the real time. As shown in Fig.1 (b), the logical time to read input is specified in the programming model. Therefore, the input is read at beginning of each real time period. However, the output is written at the 7th time instant and the 8th time instant in different real time periods, respectively. The *timed model* (e.g., the Logical Execution Model (LET) [30]) describes the system with logical duration information, which is specified by the designer [16, 30]. Since the time information is priori fixed, e.g., the times to read input and to write output are fixed in the LET model, the I/O behaviors of the LET model are predictable and composable both in the real time and the logical time [29, 30]. As shown in Fig.1 (c), the logical times to read input and write output are specified in the programming model. In different real time periods, the input is read at the beginning and the output is written at the last time instant.

Both of the logical and real time I/O behaviors have significant influences on the behaviors of the real-time system. Therefore, the predictability must not be limited to the function tasks, the I/O behaviors must be predictable as well. Though the predictability of function tasks have been researched extensively, the predictability of the I/O behaviors of a task is not well studied.

2.2. Predictable Properties of Different Behaviors

In this section, from the standpoint of emerging characteristics of CPS, we argue that both the order property and the time property of different behaviors must be predictable.

2.2.1. Predictable Properties of I/O behaviors

CPS have diverse kinds of I/Os, which must be processed timely and safely. Meanwhile, a complex CPS is always composed by different sub-systems, which are connected through I/Os. Therefore, more rigorous properties of I/O behaviors need to be predictable. We argue that the input ready time, the inputs ready order, and the time of writing output must be predictable.

Figure 2: Illustration of input-ready order and input-ready time

To be concise, we take Fig.2 for example. $A_0 \sim A_2$ are underlying implementations of actors, which are concurrent components that communicate through ports and interact according to a common pattern of interaction [43]. $i_1 \sim i_4$ are the input ports of A_0 . The sources of inputs vary from highly sensitive sensor to satellite network. The *ready time* of input i is the interval between the time when the value in the sensor (Sensor A or C) or network (Network B or D) changes and the time when the value of the input port i is modified correspondingly and ready for the use of the function task. $\langle i_j, rt_j \rangle$ represents that the time input i_j becomes ready must be earlier than time rt_j . $C_1 \sim C_5$ are function tasks, whose inputs include the external inputs (i_1, i_2, i_3 , and i_4) and the signals (s_1, s_2 , and s_3) which are written back to the main memory by its precedent tasks. The input data must be buffered in the input port unless the time an input become ready equals to the time the value in the input port is read. $s_1 \sim s_3$ are the signals emitted by function tasks. They are called as *local outputs*, because their values are only updated in the main memory and used by other tasks in the same actor. o_1 and o_2 are output ports of actor A_0 . Since their values will be broadcasted to other actors through the network, they are called as the *network outputs*.

The input ready time must be predictable. The time an input may vary greatly, because the preparation of the input may be affected by other events, such as network transmission jitter and the sensor response time jitter. An overdue input leads to the delay of the computing of the function tasks, which in turn leads to the deadline missing of the function task. For example, in Fig.2, if i_1 cannot become ready before rt_1 , task C_1 may miss its deadline.

The inputs ready order must be predictable. The first reason is because different input ready orders result in different system behaviors. The evolution of the real-time programming models shows that the I/O behaviors play a more and more important role [29]. The asynchronous model does not specify the I/O behaviors. Even though the inputs processing sequences are specified in the programs built on the synchronous model and timed model, the inputs may become ready in an unexpected order, which is different from the specification. For example, in Fig.2, to get the value of o_1 , the inputs reading sequence specified in the program is $i_1 \rightarrow i_2 \rightarrow i_3 \rightarrow i_4$, where $i_1 \rightarrow i_2$ means that i_1 is processed earlier than i_2 . If the inputs become ready in the same order as the specification, A_0 writes o_1 first, and o_2 next. o_1 triggers the events of A_1 , and o_2 triggers the events of A_2 . However, if the inputs become ready in the $i_1 \rightarrow i_3 \rightarrow i_4 \rightarrow i_2$ order, A_0 can write o_2 when i_4 is ready, but cannot write o_1 until i_2 become ready in the end. In this case, events of A_2 are triggered at first. Since A_1 and A_2 will create different chain reactions, the different triggering orders of A_1 and A_2 will significantly affect the behaviors of the system.

The second reason of the needs for inputs ready order predictability is because of the uncertainties caused by the buffer management costs for the out-of-order inputs. In Fig.2, if the function task can process the input value immediately when the input becomes ready, no buffer is needed. Otherwise, a buffer is needed to store the value of the input until it is processed. For example, if the ready time of i_4 is earlier than those of i_1 , i_2 , or i_3 , then the value of i_4 has to be buffered, and waits for the other inputs to become ready. Experiments have shown that the temporal variability caused by the unpredictable runtime system activities is more serious than the data-dependency of the task [54]. Since the buffer manager is one of the important runtime system activities [33], the unpredictable inputs ready orders decrease the predictability of the runtime system. This situation is even worse in CPS, which receive diverse kinds of inputs from the physical world.

The time of writing outputs must be predictable. The output values cannot be used until they are written back to main memory (such as values of s_1 , s_2 , and s_3) or broadcasted to other actors (such as values of o_1 and o_2). Since output is also a source of input, the predictability of outputs directly influence the predictability of inputs. However, the time of writing outputs is not fixed because of the following two reasons: *First*, in the synchronous programming model and the asynchronous model, the time to write output is not specified,

Figure 3: Execution of p and t under different schedulers

and it depends on its function task, which is highly unpredictable (Fig.1 (a) and (b)). *Second*, even though in the timed model, such as the LET model, the time to write output is pre-determined in the model (Fig.1(c)), the time of writing outputs is still not fixed, because the out writing process can be affected by hardware system, such as the memory system and the networks. Therefore, we need to define and evaluate the time predictability of the outputs.

2.2.2. Predictable Properties of Function Task Behaviors

Due to the concurrent and preemptive characteristics of CPS, we argue that the time predictability of function tasks should not be measured by the execution time, which is estimated under the uninterrupted execution assumption [28]. In addition, the execution order of tasks in a scheduling set also needs to be predictable.

The time predictability of function task must not be limited to the predictability of the execution time. For example, in Fig.3, task t and task p are two independent tasks in the same task set, which is executed periodically (10ms). The upper half and lower half of Fig.3 shows the resulting times of task p and task t in different schedulers. Whenever a scheduling event occurs, the Earliest-Deadline-First (EDF) scheduler chooses the task with closest deadline to execute in the next period. The Time-Slice scheduler runs once every time slice to choose the next task to run according to the task priority [12]. We can see that the finish times of task p and task t vary greatly under different schedulers, and even in different periods of the same scheduler. Therefore, in the multi-tasking and preemptive system, e.g., CPS, the definition of the time predictability of function tasks should take the interruptions from other tasks and the overheads of the kernel behaviors into consideration.

(a) Priority Order: $T_1 > T_2 > T_3 > T_4 > T_5 > T_6 > T_7 > T_8 > T_9$

(b) Priority Order: $T_1 > T_2 > T_4 > T_5 > T_6 > T_3 > T_9 > T_7 > T_8$

Figure 4: Scheduling anomaly while changing priority orders

The execution order of tasks in a scheduling set must be predictable. In the Preemptable, Non-migratable and Fixed priority (P/N/F) cases, the execution of independent tasks is not predictable for arbitrary priority assignments. It is predictable when the tasks are scheduled in the order in which they are released [22]. A non-predictable scheduling algorithm would cause anomalies. Fig.4 and Fig.5 show two of the famous Richard's anomalies [19]. There are 9 tasks with precedence: T_9 depends on T_1 . T_5 , T_6 , T_7 , and T_8 depend on T_4 . $\langle T_i, P_i, C_i \rangle$ represents that the priority of task T_i is P_i , and its computation time is C_i . The scheduling length of Fig.4 (a) is 12. However, when the execution order changes, the scheduling length increases to 14 (Fig.4 (b)). In Fig.5 (a), while the execution time of each task is reduced by 1 and all other parameters remain unchanged, the scheduling length increases. Among all those anomalies, we can observe the change of the execution order. However, in some anomalies, if the execution order is properly arranged, the scheduling length will not increase. For example, the execution order of Fig.5 (b) is the same with that of Fig.4 (a), the scheduling length is 10, which is shorter than the length of Fig.4 (a). Therefore, the execution order is important to make the scheduling algorithms predictable.

Though the execution order is important, it is nondeterministic because of the following reasons: *First*, if the priority is not assigned according to the release order, the execution order is unpredictable [22]. *Second*, the “best-effort” scheduler and runtime systems may change the execution order

(a) Execution time reduced: $C'_i = C_i - 1$

(b) Execution time reduced, while execute in the same order as Fig.4 (a)

Figure 5: Scheduling anomaly while reducing the execution time

dynamically in the multicore platform. As shown in Fig.5 (a), the “best-effort” scheduler chooses to execute task T_4 when processor Core-2 is free, leading to the change of execution order compared with the execution order of Fig.4 (a), and the scheduling length of Fig.5 (a) increases. *Third*, the execution order can be changed when trying to avoid hazards with mutexes, which are caused by tasks that share the same resource. For example, the key idea (e.g., the Priority Ceiling Protocol and the Priority Inheritance Protocol) to overcome deadlock and priority inversion problem is to adjust the execution order of tasks that acquire the same resource lock [18, 50]. However, the adjustment leads to the change of execution order, and reduces the predictability of the task execution in turn.

In summary, both the I/O behavior and the function task must be predictable in CPS. Both of them must have predictable time property and predictable order property.

3. Define Predictability for CPS

According to [4, 21], the notion of predictability should capture if, and to what level of precision, a specified property of a system can be predicted by a system-specific optimal analysis. To enable a concise and uniform description of predictability instances, Grund proposes a template for the definition of predictability, which should consist of three aspects: 1) **property** to be

predicted; 2) sources of **uncertainty**, and; 3) quality **measure** [21]. In this section, we analyze the sources of uncertainties of different properties, and use the template and the uncertainties to define the predictability of different properties that we summarized in the last section.

3.1. Predictability of Input Behavior

In this section, we analyze the sources of uncertainties of different kinds of inputs, and propose definitions for their predictability. According to the definition of input (Section 2.2), we classify the input into sensor and network. Since the uncertainties of network is more significant than that of sensors, we classify the sensor inputs, whose values are transmitted through network, into the network inputs.

3.1.1. Time Predictability of Sensor Input

The sensor changes its output state after a period of time delay when an input parameter changes. The delay includes the conversion time of the A/D converter and further time delays due to signal processing, for example, filter operation, outlier detection [1]. The time required for a sensor to change from its previous state to a final settled value within a tolerance band of the correct new value is called *sensor response time* [15, 55]. The sensor response time changes dynamically because it can be affected by many factors, such as the workload, construction details, properties and geometries of the sensor's internal material, and the properties of the medium surrounding the sensor.

We use the variability of the sensor response time to measure the ready time predictability of the sensor input. Let I and S denote all the possible inputs and states of the sensor. The ready time predictability of the sensor input is defined as:

$$Pr_{sensor}(I, S) := \min_{i_1, i_2 \in [1, N_I]} \min_{j_1, j_2 \in [1, N_S]} \frac{T_r(I_{i_1}, S_{j_1})}{T_r(I_{i_2}, S_{j_2})} \quad (1)$$

where $I_{i_1}, I_{i_2} \in I$ and $S_{j_1}, S_{j_2} \in S$. N_I and N_S are the numbers of sensor inputs I and sensor states S , which are determined theoretically. $T_r(I_i, S_j)$ is used to calculate the sensor response time when the sensor input parameter is I_i and the sensor is at the S_j state. T_r can be calculated through theoretical approaches [26]. T_r can also be determined by the combination of theoretical approaches and experiment approaches, because properties that affect the sensor response time are not known thoroughly and may change under

(a) Event-Triggered Communication

(b) Time-Triggered Communication

Figure 6: Event-Triggered and Time-Triggered Communication Jitter

process operating or aging conditions [24, 51]. The quotient is the quality measure: $Pr_{sensor} \in (0, 1]$, where the larger Pr_{sensor} is, the more predictable the ready time of the sensor input is. If Pr_{sensor} is close to 1, the sensor is slightly affected by its environments and the variability of the sensor response time is small. In this case, the time to process the input can be set compactly, so that the values in the input port can be processed as soon as possible. This can improve the predictability of the input-determined programs. In addition, this can reduce the time to use buffers, which can contribute to the predictability of the runtime systems.

3.1.2. Time Predictability of Network Input

From the temporal point of view, communication services are classified into Event-Triggered (ET) communication and Time-Triggered (TT) communication [35]. In this section, we analyze the time uncertainties of the ET communication and TT communication, respectively, and propose metrics to define the ready time predictability of the network input.

In an Event-Triggered communication system, a sender sends a message

whenever a significant event occurs at the sender, and places the message in a queue at the senders site until the basic message transport service is ready to transport the message to the receiver. After arrival of the message at the receiver, the message is placed in a receiver queue until the receiver consumes the message. Typical ET communication protocols include Ethernet protocol [46], Controller Area Network (CAN) protocol [13], and User Datagram Protocol (UDP) protocol from the Internet suite protocol. The delay of the ET communication protocols can be affected by the bus workload, the message priority, the data rate and so on [37]. We take the TCP and UDP for example. As shown in Fig.6 (a), messages arrive through a TCP channel experience different delays though they are received in the right order. The delays of different messages vary greatly. No messages are lost during the transmission. If the messages are transmitted through a UDP channel, though the delays are smaller, some messages are lost. Other ET communication protocols try to reduce the loss or the delay. However, protocols preventing loss do so by re-transmission which creates variable delay or jitter, one cannot eliminate both [29]. The network jitter caused by the variability of the delays seriously reduce the predictability of ET real-time networks. Therefore, the influence of the network jitter on the predictability of network inputs needs to be measured.

In a Time-Triggered communication system, the sender and receiver(s) agree a priori on a cyclic time-controlled conflict-free communication schedule for the sending of time-triggered messages [35]. Typical TT communication protocols include Time-Triggered protocol (TTP) [36], Time-Triggered Ethernet (TTEthernet) [34], and FlexRay [9]. Even though the TT communication is claimed to be predictable, the reality is not as predictable as what the TT communication claims. The first and foremost thing that affects the predictability of the TT communication protocol is the synchronization error [37]. In addition, the predictability can also be affected by technique details. We take the TTP for example. TTP uses the message description list (MEDL), which is constructed off-line and loaded on each TTP controller before operation starts, to specify which node will transmit which message at what time. The MEDL describes the operation of the bus on a common global timeline, which is produced by the clock synchronization protocol. Time is divided into cycles, rounds, and slots (Fig.6(b)). Each cycle contains a number of rounds and each round a number of slots. Cycles are repeated as long as the system runs, in exactly the same way. Rounds have the same duration, whereas slots within a round may have different durations. Each slot

is assigned to a node, which transmits exclusively during that slot. Within a slot, a node transmits a frame, which contains one or more messages. We assume that the number of messages of each frame is the same. The TTP guarantees that (only) one node sends a frame in its slot. However, the starting and ending times of transmission are not exactly the same in each slot of different rounds and different cycles. In Fig.6(b), t_i is the transmission ending time variances between different slots of different rounds. Even though the time variances of the TT communication protocols are smaller than that of the ET communication protocols in most cases, the variances should be carefully measured to assess their influences on the predictability of the TT communication protocols for the time safety critical CPS.

We use the the network delay to measure the time predictability of the network inputs. We assume that there are M flows of messages need to be transmitted over the network. The delay set of all the messages is D , which can be analyzed statically. T_d is the delay of a flow of message. The predictability of network input is defined as:

$$Pr_{network}(D) := \min_{1 \leq i, j \leq M} \frac{T_d(JT_i, LD_i, SD_i, WD_i)}{T_d(JT_j, LD_j, SD_j, WD_j)} \quad (2)$$

where $T_d(JT, LD, SD, WD)$ is used to calculate the network input delay. JT_i is the release jitter of the i_{th} flow of message. LD_i is the transmission time on links along the considered path. SD_i is the delay caused by switching latency. WD_i is the waiting delay caused by competitions with other frames in the output buffers. The quantification over these four kinds of delays in T_d capture the uncertainties of network delay. The way T_d is calculated is highly dependent on the model of the network and the environments [3, 6, 17, 44, 49, 57, 58]. The quotient is the quality measure: $Pr_{network} \in (0, 1]$, where the larger $Pr_{network}$ is, the more predictable the network input is. The network are the major sources of input uncertainties, therefore, if $Pr_{network}$ is close to 1, the predictability of the inputs can be improved significantly, which in turn increases the predictability of the system.

3.1.3. Ready Order Predictability of Inputs Set

In this section, we introduce a method to determine all the possible ready orders based on the ready times of different inputs at first. Then, we propose a method to calculate the buffer costs of the inputs ready order. In the end, we define the predictability of the inputs ready order based on buffer costs.

Figure 7: Best Case and Worst Case Ready Times of different Inputs in Fig.2

Find All the Possible Input Ready Orders. Assume that RT_I is the set of possible ready times of an inputs set. $RT_I = \{RT_i \mid i \in I\}$, where I is the input set and i is an input of I . RT_i is the set of response times of input i . $RT_i = \{rt \mid rt_i^B \leq rt \leq rt_i^W, rt_i \in \mathbb{R}\}$, where rt_i^B and rt_i^W are the Best Case Ready Time and the Worst Case Ready Time of input i , respectively. We introduce Theory 1 to limit the ready orders of I .

Theory 1. $\forall i, j \in I$, if $rt_i^W < rt_j^B$, then $RT_i \cap RT_j = \Phi$, and input i becomes ready earlier than input j , there must exist $O_i < O_j$, which means that input i must be at the front of input j in the inputs ready order.

The ready order of I cannot violate the order limited by Theory 1. Therefore, the problem to find the possible ready orders of I can be solved by finding all the possible orders of a partially ordered sequence of vertexes. We use the Topological Sorting to find all the possible input ready orders [14]. We use RT_I to construct the Directed Acyclic Graph (DAG), i.e., G . Let $G = (I, E)$, where I is the inputs set of the actor, and E is the set of directed edges generated according to the following rule: $\forall i, j \in I$, if $O_i < O_j$, add an directed edge from vertex i to vertex j . The possible orders can be found by algorithms shown in [32], which can generate all the possible solutions for a topological sort.

We take Fig.7 for example. Assume that $rt_{i_1}^B = 3, rt_{i_1}^W = 7; rt_{i_2}^B = 9, rt_{i_2}^W = 21; rt_{i_3}^B = 5, rt_{i_3}^W = 11; rt_{i_4}^B = 13, rt_{i_4}^W = 24(ms)$. According to Theory 1, the orders that the inputs become ready must satisfy the following rules: $O_{i_1} < O_{i_2}$, $O_{i_1} < O_{i_4}$, and $O_{i_3} < O_{i_4}$. We use the above rules and I to construct the DAG. i_1, i_2, i_3 , and i_4 are the vertexes of the DAG. Since $O_{i_1} < O_{i_2}$, a directed edge is added from i_1 to i_2 . The same goes for the directed edge

Figure 8: Find All the Possible Input Ready Orders by the Topological Sorting Algorithm

from i_1 to i_4 and the edge from i_3 to i_4 . Fig.8 shows the DAG built on RT_I and the way to find all the possible inputs ready orders. According to algorithms proposed in [32], all the possible ready orders are as following: $S_1: i_3 \rightarrow i_1 \rightarrow i_2 \rightarrow i_4$, $S_2: i_3 \rightarrow i_1 \rightarrow i_4 \rightarrow i_2$, $S_3: i_1 \rightarrow i_2 \rightarrow i_3 \rightarrow i_4$, $S_4: i_1 \rightarrow i_3 \rightarrow i_2 \rightarrow i_4$, and $S_5: i_1 \rightarrow i_3 \rightarrow i_4 \rightarrow i_2$.

Calculate the Buffer Costs of Each Inputs Ready Order. The buffer cost represents the influence of the buffer to the system's predictability. It is not the number of buffers, because the buffer affects the system's predictability as long as it exists [54]. Therefore, we use a buffer's accumulated influence on the system to measure the buffer cost. Assume that the cost of each buffer operation is the same, the *buffer cost* is defined as follows: if a number of n inputs values are buffered while reading input i , the buffer cost while reading input i is n . The buffer costs of the inputs ready order is the sum of buffer costs while reading all the inputs.

We take the ready order S_2 (shown in Fig.8) for example. The ready order of S_2 is $i_3 \rightarrow i_1 \rightarrow i_4 \rightarrow i_2$. The buffer costs that are needed to process S_2 is calculated in the way shown in Fig.9. At the 1st time instant, the actor needs to read i_1 , which is not ready yet. However, since i_3 is ready now, one buffer cost is required to store its value. At the 2nd time instant, the actor reads i_1 again, which is ready now. Since i_3 is still in the buffer, one buffer cost is needed to maintain the buffer. At the 3rd time instant, the actor reads i_2 , which is not ready yet. Since i_4 becomes ready at this instant, a new buffer is required. i_3 is still in the buffer, therefore two buffer costs are needed at this instant. At the 4th time instant, actor reads i_2 , which becomes ready just in

Time Instants	Read	Inputs			Buffer Costs
		Ready	Unready	Buffered	
1	$i_1 \times$	i_3	i_1, i_2, i_4	i_3	1
2	$i_1 \checkmark$	i_3, i_1	i_2, i_4	i_3	1
3	$i_2 \times$	i_3, i_4	i_2	i_3, i_4	2
4	$i_2 \checkmark$	i_3, i_4, i_2	NULL	i_3, i_4	2
5	$i_3 \checkmark$	i_3, i_4	NULL	i_4	1
6	$i_4 \checkmark$	i_4	NULL	NULL	0

Figure 9: Calculate the Buffer Costs of $S_2 : i_3 \rightarrow i_1 \rightarrow i_4 \rightarrow i_2$

time. Therefore, two buffer costs are in need to maintain the buffers which are used by i_3 and i_4 . At the 5th time instant, actor reads i_3 , and releases the buffer for i_3 . Therefore, only the buffer cost for i_4 is in need. At the 6th time instant, actor reads i_4 , and all the buffers are released. No buffer costs are in need at this instant. Therefore, if the inputs become ready in the S_2 order, the buffer costs is the sum of the costs in each time period, namely, 7.

In the following, we present a generalized method to calculate the buffer costs of a determined inputs ready order. Let I denote the set of all the N inputs. The states of I are stored in the ready states matrix, $S_r = [s_1, s_2, \dots, s_j, \dots, s_N]^T$, where $s_j = [s_{i,1}, s_{i,2}, \dots, s_{i,j}, \dots, s_{i,N}]$. s_j is a sequence of input ready states when the j th input becomes ready. If input i_k of s_j is ready, then $s_{j,k} = 1$, or $s_{j,k} = 0$. The ready states matrix of S_2 (Fig.8) is shown as follows:

$$S_r = \begin{matrix} & i_1 & i_2 & \cdots & i_N \\ \begin{matrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{matrix} & \begin{pmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,N} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ s_{N,1} & s_{N,2} & \cdots & s_{N,N} \end{pmatrix} \end{matrix}, S_2 = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{pmatrix}$$

We propose Alg.1 to calculate the buffer costs of the inputs ready order. Given the states matrix S_r , the number of inputs N , assume that the inputs are read from the 1st input to the N th input in monotonous order. Alg.1 simulates the input reading process while the ready order is S_r . The value of i in Alg.1 is the index of the time instants, and *read* is used to record which

input should be read at this instant. Codes between line 5 and line 8 are used to change the input state if the input is ready and has been read. Codes between line 9 and line 11 are used to calculate the buffer costs. In the worst case, in which the inputs become ready in the inverse order compared with the order which is specified in the programs, the outer loop executes $2 \cdot N$ times. In this case, the codes between line 5 and line 8 execute $(N+1)N/2+N$ times, and codes between line 9 and line 11 execute $2N^2$ times. Therefore, the worst case time complexity of Alg.1 is $((N+1)N/2 + N) + 2N^2$, which equals to $O(N^2)$, where N is the number of inputs.

Algorithm 1: Calculate the Buffer Costs of the Input Ready Order S_r

Data: State Matrix, S_r ; Number of Inputs, N

Result: Buffer Costs, buf

```

1   $read = 1, i = 1, j = 1, buf = 0;$ 
2  while  $true$  do
3      if  $read == N$  then
4          break;
          /* if the input to be read is ready now, then read it and set  $S[*][read]$ 
          as 2 to indicate that it has been read. */
5      if  $S_r[i][read] == 1$  then
6          for  $j = i; j \leq N; j++$  do
7               $S_r[j][read] = 2;$ 
8               $read++;$ 
          /* If the input is ready, but cannot be read, then a buffer has to be
          added. */
9      for  $j = 1; j \leq N; j++$  do
10         if  $S_r[i][j] == 1$  then
11              $buf++;$ 
12     if  $i < N$  then
13          $i++;$ 
14     else
15          $i = N;$ 
16 return  $buf;$ 

```

Define the Predictability of the Inputs Ready Order. Based on Alg.1, we can calculate the buffer costs of every ready order shown in Fig.8. The buffer

costs of S_1, S_2, S_3, S_4 , and S_5 are 4, 7, 0, 3, and 6, respectively. We can see that the buffer costs vary greatly among different ready orders. Since the buffer costs significantly affect the predictability of the system [33, 54], we use the quotient of the minimum over the maximum buffer costs to measure the predictability of the inputs order.

Let S denote the set of inputs ready orders that are calculated through the way shown in Fig8. Assume that Buf_{S_i} is the buffer costs of S_i , which is calculated by Alg.1. If $\exists S_i \in S \wedge Buf_{S_i} = 0$, S is refined as $\hat{S} = \{S_r \mid S_r \in S \wedge Buf_{S_r} \neq 0\}$, because the zero buffer cost does not affect the system's predictability. If the cardinality of $\hat{S}$ is zero, the ready order predictability is 1, else the input ready order predictability is defined as:

$$Pr_{InputsOrder}(\hat{S}) := \min_{S_i, S_j \in \hat{S}} \frac{Buf_{S_i}}{Buf_{S_j}} \quad (3)$$

The quotient is the quality measure: $Pr_{InputsOrder} \in (0, 1]$, where the larger $Pr_{InputsOrder}$ is, the more predictable the inputs ready order is. However, $Pr_{InputsOrder} = 1$ does not necessarily mean that there is only one order in S , because some different orders may need the same buffer costs, in which case we think that these orders affect the predictability of the system at the same level. A perfect predictable input ready order does not necessarily mean that the inputs become ready in the ideal order every time. Rather, it emphasizes that the orders in which the inputs become ready are the same under different ready times of the inputs. In this case, since the buffer costs to read the inputs are the same, they have the same influence on the system. This is good for the predictability, because we can confidentially tell how the system is affected by the inputs, and try to fix the bad effects. More importantly, if $Pr_{InputsOrder}$ is close to 1, the input-determined programs have more predictable behaviors, and more reliable composition and verification results [40]. Otherwise, if $Pr_{InputsOrder}$ is close to 0, the predictability of the input-determined programs and the reliability of the composition and verification results are badly affected by the inputs ready order. In this case, the calculation and definition in this section can help to find the bottleneck and provide ideas to improve the predictability, e.g., reducing the number of ready time intersections shown in Fig.7.

3.1.4. Predictability of Inputs Set

Compared with the network delay, the delay of sensor is shorter in most cases. However, that does not mean that the predictability of network is more important than that of the sensor to CPS, since any delay that outstrips the predictability may lead to the disaster of the time critical CPS. Therefore, the predictability of the inputs set depends on the factor who has the worst predictability. Taking the inputs ready order into consideration, the predictability of the inputs set is defined as:

Definition 1. Given a platform $\mathcal{P}$, and its input set $\mathcal{I}$. Its sensor inputs set is $\mathcal{I}_S$, and its network inputs set is $\mathcal{I}_N$. The predictability of input set $\mathcal{I}$ is:

$$Pr_{\mathcal{I}} := \min(\min_{i_s \in \mathcal{I}_S}(Pr_{i_s}), \min_{i_n \in \mathcal{I}_N}(Pr_{i_n}), Pr_{InputsOrder}) \quad (4)$$

where Pr_{i_s} is the predictability of sensor input i_s (Equation 1), Pr_{i_n} is the predictability of network input i_n (Equation 2), and $Pr_{InputsOrder}$ is the predictability of inputs ready order of $\mathcal{I}$ (Equation 3). If $Pr_{\mathcal{I}}$ is close to 1, the inputs are highly predictable, and the system tends to have more predictable behaviors and reliable verification results, and can be composed more easily. However, if $Pr_{\mathcal{I}}$ is close to 0, the inputs are badly predictable. In this case, the testing and verification of CPS are very hard and unreliable, and it is very hard to ensure the safety of CPS. We need to figure out the critical factor that depresses the input predictability according to Equation 4, and spare no efforts to improve the predictability of that factor.

3.2. Predictability of Output Ports

According to [31], output is defined as writing the results of the computation to one or more nodes, which may be devices and/or main memory. This section discusses the sources of uncertainties of writing outputs, and proposes definitions for the output predictability.

3.2.1. Time Predictability of Local Output

If the output of a task is only used by other tasks in the same node, the output is called *local output*, whose value should be written back into memory for the usage of other tasks. For example, in Fig.2, task C_2 depends on the computation result of task C_1 , to ensure the consistency of the memory system, C_2 will wait until C_1 finishes writing s_1 into the main memory. Since only the value of the local platform is updated, the unpredictability

of the local output mainly comes from the memory access latency [56]. We use the latency of updating the value in main memory to define the time predictability of the local outputs:

Definition 2. *In platform $\mathcal{P}$, the latency to update the memory value is l_{ch} if all caches hit, and the latency is l_{cm} if all caches miss. Once starting to write output, the time predictability of the local output is:*

$$Pr_{LocalOut} := \frac{l_{ch}}{l_{cm}} \quad (5)$$

The quotient is the quality measure: $Pr_{LocalOut} \in (0, 1]$. It is the quotient of the latency when cache hit over the latency when cache miss to update memory value. However, the reality would be much more complicated because of the great uncertainty of the memory system. For example, when the processor is ready to write memory, the updating job has to wait if the main memory is refreshing, leading to the unpredictability of the output. The predictability of the memory system can be improved by adopting the scratchpad memory[5, 45]. Since the local output of the precedent task is used as the input of the subsequent task in the same node, therefore, if $Pr_{LocalOut}$ is close to 1, the predictability of the subsequent task is improved significantly. In addition, a highly predictable local output can reduce the data synchronization cost between the precedent task and the subsequent task, and thus increase the predictability and reliability of the system.

3.2.2. Time Predictability of Network Output

If the output value needs to be broadcasted to other sink(s) through network, the output is called as *network output*, whose unpredictability is mainly caused by the variability of network delays of different receivers. Different from the network input, the network output have to update values in more than one remote receivers. Therefore, the time predictability of network outputs can be measured by the variability of the intervals between the earliest time and the latest time when the sinks receive the message:

Definition 3. *Given a platform $\mathcal{P}$, and its sender S . The receiver set is $\mathcal{R}$, which has N receivers. A number of M flows of messages need to be sent to each receiver. The delay of transmission to $\mathcal{R}$ is $\mathcal{D}$. The time predictability*

of network outputs of platform $\mathcal{P}$ is:

$$Pr_{NetOut}(\mathcal{R}) := \min_{1 \leq i_1, i_2 \leq N} \min_{1 \leq j_1, j_2 \leq M} \frac{T_d(JT_{j_1}^{i_1}, LD_{j_1}^{i_1}, SD_{j_1}^{i_1}, WD_{j_1}^{i_1})}{T_d(JT_{j_2}^{i_2}, LD_{j_2}^{i_2}, SD_{j_2}^{i_2}, WD_{j_2}^{i_2})} \quad (6)$$

where $T_d(JT_j^i, LD_j^i, SD_j^i, WD_j^i)$ is used to calculate the latency of the j^{th} flow of messages which are sent to the i^{th} receiver. JT , LD , SD , and WD are the four kinds of network delays which are used to capture the network uncertainty (Section 3.1.2). The property to predict is the network delay to of different messages to different receivers. Definition 3 can also be used to measure the network output which has only one remote receiver. In this case, N is 1, and Pr_{NetOut} is the quotient of the best case delay over the worst case delay to the remote receiver. The quotient is the quality measure of the predictability of the network output: $Pr_{NetOut} \in (0, 1]$, where the larger Pr_{NetOut} is, the better the time predictability of the network output is. If Pr_{NetOut} is close to 0, we must find out the receiver which has the worst predictability according to Equation 6, and improve the predictability of the network transmission to that receiver.

3.3. Predictability of Function Tasks

Considering the concurrent and preemptive characteristics of CPS, we propose to use the task response time to define the time predictability of function tasks in this section. We define the order predictability of tasks set based on the distance between the actual execution order and the ideal execution order. Tasks discussed in this section are Preemptive, Non-Migratable, and Fix-Priority (P/N/F) tasks.

3.3.1. Time Predictability of Function Tasks

Due to the multitasking, high concurrency, and frequently preemptive characteristics of CPS, the measure of the time predictability of function tasks should take the interferences from other tasks into consideration. The task response time is defined as the time between the release of a task and its corresponding completion [10]. The estimation of response time includes the execution time, the preemption of other tasks, and interferences from OS kernel. Therefore, we use the response time, i.e., Best Case Response Time (BCRT) and Worst Case Response Time (WCRT) to define and measure the time predictability of individual function task and tasks set.

Calculation of WCRT and BCRT. Burns proposed the methods to estimate the WCRT of a task in the preemptive priority based scheduling algorithms [11]. Task i is assumed to consist of an infinite number of invocation requests, each separated by T_i , which is the minimum inter-arrival time for the events that releases the task. Each invocation of task i requires WC_i computation time in the worst case. During this time, the task cannot be preempted. A ceiling priority protocol is used to solve the priority inversion problem, which gives rise to the blocking time. WB_i is the maximum time task i can be blocked while waiting for a lower priority task. The WCRT of task i is calculated as [11]:

$$WR_i = WB_i + WC_i + \sum_{j \in hp(i)} \left\lceil \frac{WR_i}{T_j} \right\rceil WC_j + \left\lceil \frac{WR_i}{T_{clk}} \right\rceil C_{clk} + \sum_{f \in fpt} \left\lceil \frac{WR_i}{T_f} \right\rceil C_{per} \quad (7)$$

where WR_i is the WCRT of task i , and $hp(i)$ is the set of tasks who have higher priorities than task i . Assume that tasks are on the delay queue but none are removed, C_{clk} is the overhead occurring on each interrupt, C_{per} is the cost of moving one task from the delay-queue to run-queue, and fpt is the set of fictitious periodic tasks, which have the same period with task i . WR_i can be calculated through the iterative process as explained in [11].

The calculation of BCRT is researched in [10, 48], which take account of the preemptions of higher priority tasks. However, as long as there are preemptions, the runtime overheads (e.g., removing tasks from delay-queue to run-queue) are unavoidable. Therefore, the runtime system overheads should also be considered when calculating the BCRT. The BCRT is calculated in the following way:

$$BR_i = BB_i + BC_i + \sum_{j \in hp(i)} \left\lceil \frac{BR_i}{T_j} \right\rceil BC_j + \left\lceil \frac{BR_i}{T_{clk}} \right\rceil C_{clk} + \sum_{f \in fpt} \left\lceil \frac{BR_i}{T_f} \right\rceil C_{per} \quad (8)$$

BR_i is the best case response time of task i . BC_i is the best case computation time of task i , and BB_i is the minimum time task i can be blocked. The other parameters of Equation 8 have the same meaning with that of Equation 7. $\left\lceil \frac{BR_i}{T_{clk}} \right\rceil C_{clk}$ and $\sum_{f \in fpt} \left\lceil \frac{BR_i}{T_f} \right\rceil C_{per}$ take the runtime overheads and interruptions of other tasks into consideration, respectively.

It should be noted that methods to calculate BCRT and WCRT vary greatly in different situations, such as different scheduling algorithms. In this paper, we use the classical methods to show the basic ideas and the sources of uncertainties of the response time. However, the specific methods to estimate BCRT and WCRT should be determined by the characteristics of the tasks and their execution environments.

Time Predictability of Individual Task. We use the quotient of the BCRT over the WCRT of an individual task to define its time predictability.

Definition 4. Let $\mathcal{T}$ denote the tasks set, whose tasks can be executed concurrently. For any task $\tau_i \in \mathcal{T}$, assume that its BCRT is BR_{τ_i} , and its WCRT is WR_{τ_i} . The time predictability of task τ_i is:

$$Pr_{\tau_i} := \frac{BR_{\tau_i}}{WR_{\tau_i}} \quad (9)$$

where BR_{τ_i} and WR_{τ_i} are calculated through Equation (8) and Equation (7), respectively. The quotient is the quality measure: $Pr_{\tau_i} \in (0, 1]$, where the higher Pr_{τ_i} is, the more predictable task τ_i is. If the Pr_{τ_i} is close to zero, the time predictability of task τ_i is highly unpredictable. Since Definition 4 captures the sources of uncertainties of response time, we can use it to find the critical uncertainty sources and improve its time predictability. Compared with the definitions in [21, 28, 53], Definition 4 introduces the interferences from other tasks and overheads of the runtime systems. Therefore, Definition 4 is more suitable and practical for the concurrent and preemptive systems.

Time Predictability of Tasks Set. The time predictability of tasks set is affected by various factors, e.g., the task characteristic, runtime system, and scheduler [47]. Since the response time reflects the influences of those factors, we use the response time to define the time predictability of tasks set.

Definition 5. Let $\mathcal{T}$ denote the tasks set, whose tasks can be executed concurrently. For any task $\tau_i \in \mathcal{T}$, assume that its BCRT is BR_{τ_i} , and its WCRT is WR_{τ_i} . The time predictability of tasks set $\mathcal{T}$ is:

$$Pr_{\mathcal{T}}(\mathcal{T}) := \frac{\max_{\tau_i \in \mathcal{T}}(BR_{\tau_i})}{\max_{\tau_j \in \mathcal{T}}(WR_{\tau_j})} \quad (10)$$

$\max_{\tau_i \in \mathcal{T}}(BR_{\tau_i})$ and $\max_{\tau_j \in \mathcal{T}}(WR_{\tau_j})$ are the earliest time and the latest time, at which all the tasks in $\mathcal{T}$ complete. Note that they are not necessarily equal to the BCRT and the WCRT of the lowest priority task, respectively. Their values depend on the scheduling algorithms, properties of the tasks, and how BCRT and WCRT are calculated. The quotient is the quality measure: $Pr_{\mathcal{T}} \in (0, 1]$. The smaller $Pr_{\mathcal{T}}$ is, the worse the time predictability of the

tasks set is, and the harder it is to determine the periods and deadlines of $\mathcal{T}$. The designer has to face a dilemma: on the one hand, to guarantee the safety, choose a higher performance platform, which may run at lower utilization ratio because the tasks may completed earlier in most cases; on the other hand, to reduce the cost, set a risky deadline, which is not safe in the worst cases. If $Pr_{\mathcal{T}}$ is close to 1, which means that the completion time of the tasks set is highly predictable, the durations of this tasks set can be set compactly and safely with high confidence.

3.3.2. Execution Order Predictability of Tasks Set

In this section, we propose a method to describe the tasks execution order, and introduce the ideal execution order at first. Then, we introduce a theory to calculate the order distance between the actual execution order and the ideal execution order. At last, we use the variability of the execution order distances to define the predictability of tasks execution order.

Ideal Execution Order of Tasks Set. According to Theorem 4.2 of [22], for a priority-driven scheduling algorithm, the execution of tasks is predictable only if the priorities of independent tasks are assigned on the FIFO basis (i.e., the earlier the release time, the higher the priority). Therefore, we take the order in which tasks are released as the *ideal execution order*.

Given a set of N tasks, denoted by $\mathcal{T} = \{\tau_i \mid i \in [1, N]\}$, where τ_i is a task. Let $TOI_{\mathcal{T}}$ denote the ideal execution order of the tasks in $\mathcal{T}$. $TOI_{\mathcal{T}} = \{\tau_1^{\mathcal{T}}, \tau_2^{\mathcal{T}}, \dots, \tau_N^{\mathcal{T}}\}$, where $\forall i, j \wedge i, j \in [1, N]$, $\tau_i^{\mathcal{T}} \prec \tau_j^{\mathcal{T}}$, which means that τ_i is executed before τ_j when $i < j$. Since different tasks can be executed parallelly at the multicore platforms, the ideal execution order is refined as:

$$\widehat{TOI}_{\mathcal{T}} = \left\{ \underbrace{\{\tau_1^{\mathcal{T}}, \tau_2^{\mathcal{T}}, \dots, \tau_{k_1}^{\mathcal{T}}\}}_{\tau_1^{\mathcal{T}'}} \dots, \underbrace{\{\tau_{k_{j-1}+1}^{\mathcal{T}}, \tau_{k_{j-1}+2}^{\mathcal{T}}, \dots, \tau_{k_j}^{\mathcal{T}}\}}_{\tau_j^{\mathcal{T}'}} \dots, \underbrace{\{\tau_{k_{n-1}+1}^{\mathcal{T}}, \tau_{k_{n-1}+2}^{\mathcal{T}}, \dots, \tau_{k_n}^{\mathcal{T}}\}}_{\tau_n^{\mathcal{T}'}} \right\}$$

where $n \leq N$, and $\tau_j^{\mathcal{T}'} \in \widehat{TOI}_{\mathcal{T}}$. $\widehat{TOI}_{\mathcal{T}}$ is strictly partial ordered. $\widehat{TOI}_{\mathcal{T}}$ is the *ideal execution order* if it meets the following conditions: $\forall \tau_i, \tau_j \in \mathcal{T}, \exists i', j' \in [1, n] \wedge \tau_i \in \tau_{i'}^{\mathcal{T}'} \wedge \tau_j \in \tau_{j'}^{\mathcal{T}'}$, if τ_i is released before τ_j , then $\tau_{i'}^{\mathcal{T}'} \prec \tau_{j'}^{\mathcal{T}'}$; if τ_i and τ_j are released at the same time, then $i' = j'$, namely, τ_i and τ_j are in the same element of $\widehat{TOI}_{\mathcal{T}}$. For example, we assume that the execution order shown in Fig.4 a) is the ideal execution order of the 9 tasks that we use in Fig.4 and Fig.5. Let T denote the tasks set composed by the 9 tasks.

The ideal execution order of T is:

$$\widehat{TOI}_T = \left\{ \underbrace{\{T_1, T_2, T_3\}}_{\tau_1^{T'}}, \underbrace{\{T_4\}}_{\tau_2^{T'}}, \underbrace{\{T_9\}}_{\tau_3^{T'}}, \underbrace{\{T_5, T_6\}}_{\tau_4^{T'}}, \underbrace{\{T_7, T_8\}}_{\tau_5^{T'}} \right\}$$

The actual execution order of $\mathcal{T}$ is denoted by $TOA_{\mathcal{T}} = \{\tau_1^A, \tau_2^A, \dots, \tau_N^A\}$. It can be refined as $\widehat{TOA}_{\mathcal{T}}$ in the similar way with the refinement of $TOI_{\mathcal{T}}$. For example, the actual execution orders of Fig.5 a) and b) are:

$$\begin{aligned} \widehat{TOA}_T^a &= \left\{ \underbrace{\{T_1, T_2, T_3\}}_{\tau_1^{A'}}, \underbrace{\{T_4\}}_{\tau_2^{A'}}, \underbrace{\{T_5, T_6, T_7\}}_{\tau_3^{A'}}, \underbrace{\{T_8, T_9\}}_{\tau_4^{A'}} \right\} \\ \widehat{TOA}_T^b &= \left\{ \underbrace{\{T_1, T_2, T_3\}}_{\tau_1^{A'}}, \underbrace{\{T_9, T_4\}}_{\tau_2^{A'}}, \underbrace{\{T_6, T_5\}}_{\tau_3^{A'}}, \underbrace{\{T_7\}}_{\tau_4^{A'}}, \underbrace{\{T_8\}}_{\tau_5^{A'}} \right\} \end{aligned}$$

Calculate the Tasks Execution Order Distances. If two tasks are executed in a different order from the ideal order, a task *execution order inversion* (EOI) happens. Theory 2 is proposed to judge whether an EOI occurs.

Theory 2. Given a set of tasks $\mathcal{T}$, its ideal execution order is $\widehat{TOI}_{\mathcal{T}}$, and its actual execution order is $\widehat{TOA}_{\mathcal{T}}$. $\forall \tau_i, \tau_j \in \mathcal{T}$, a task execution order inversion (EOI) happens only if the following requirements are met:

- (1) $\tau_i \in \tau_{x_1}^{T'} \wedge \tau_{x_1}^{T'} \in \widehat{TOI}_{\mathcal{T}}, \tau_i \in \tau_{x_2}^{A'} \wedge \tau_{x_2}^{A'} \in \widehat{TOI}_{\mathcal{T}};$
- (2) $\tau_j \in \tau_{y_1}^{T'} \wedge \tau_{y_1}^{T'} \in \widehat{TOI}_{\mathcal{T}}, \tau_j \in \tau_{y_2}^{A'} \wedge \tau_{y_2}^{A'} \in \widehat{TOI}_{\mathcal{T}};$
- (3) $\tau_{x_1}^{T'} < \tau_{y_1}^{T'} \wedge \tau_{x_2}^{T'} > \tau_{y_2}^{T'} \parallel \tau_{x_1}^{T'} > \tau_{y_1}^{T'} \wedge \tau_{x_2}^{T'} < \tau_{y_2}^{T'}.$

Fig.10 shows how to calculate the number of EOIs of an actual execution order. In $\widehat{TOA}_T^a$, T_8 and T_9 are executed parallelly in different cores, therefore, $\tau_4^{A'}$ can be reordered as: $\{T_9, T_8\}$. Therefore, compared with $\widehat{TOI}_T$, $\widehat{TOA}_T^a$ schedules T_9 after T_5, T_6 , and T_7 . According to Theory 2, there are a number of 3 EOIs in $\widehat{TOA}_T^a$. In $\widehat{TOA}_T^b$, since the tasks in $\tau_2^{A'}$ and tasks in $\tau_3^{A'}$ are executed parallelly in different cores, therefore, $\tau_2^{A'}$ can be reordered

Figure 10: Calculation of the Inversion Number of $\widehat{TOA}_T^a$ and $\widehat{TOA}_T^b$

$\{T_4, T_9\}$ and $\tau_3^{A'}$ can be reordered $\{T_5, T_6\}$. Therefore, according to Theory 2, $\widehat{TOA}_T^b$ has the same order with $\widehat{TOI}_T$.

We define the *execution order distance* from the actual order to the ideal order as the number of execution order inversions of an actual execution order. Therefore, the execution order distance of $\widehat{TOA}_T^a$ and $\widehat{TOA}_T^b$ are 3 and 0, respectively.

Define the Tasks Execution Order Predictability. We use the quotient of the minimum execution order distance over the maximum execution order distance to define the tasks execution order predictability of tasks set $\mathcal{T}$.

Definition 6. Let V_{OD} denote the set of execution order distances of all the actual execution order. If $\exists v_i \in V_{OD} \wedge v_i = 0$, refine V_{OD} as $\widehat{V}_{OD} = \{v_j \mid v_j \in V_{OD} \wedge v_j \neq 0\}$. If the cardinality of $\widehat{V}_{OD}$ is zero, the predictability of the execution order is 1, else it is defined as:

$$Pr_{TaskOrder}(\widehat{V}_{OD}) := \min_{v_i, v_j \in \widehat{V}_{OD}} \frac{v_i}{v_j} \quad (11)$$

The quotient is the quality measure: $Pr_{TaskOrder}(\widehat{V}_{OD}) \in (0, 1]$, where 1 means perfectly predictable. In Definition 6, we refine V_{OD} to $\widehat{V}_{OD}$ to eliminate the order which equals to the ideal order, because in that case, it has no effects on the predictability of task execution. If the execution order is close to 1, execution order of the task set is highly predictable, and the probability to incur scheduling anomalies is easy to be eliminated as we explained in

Section 2.2.2. Also, a high predictable execution order allows us to design effective methods to avoid the hazards with mutex, e.g., priority inversion, and deadlock. It should be noted that, a perfectly predictable execution order does not necessarily mean that the actual order is same with the ideal order. However, since the actual execution order is highly predictable in that case, we are able to regulate the actual order by reasonably changing the parameters of tasks (deadlines, periods, and release time, etc.) and scheduling algorithms to achieve predictable execution of the tasks set.

4. Related Work

The problem of predictability is firstly discussed in [52], which claims that the predictability should be possible to show, demonstrate, and prove. Henzinger formalizes the notion of predictability as a form of determinism [25]. Jensen thinks that something is predictable to the degree that it can be shown in advance [27]. According to Jensen, the predictability is a continuum, having maximum predictability - called determinism - as one end-point. The minimum predictability end-point is that nothing is known at priori about the thing being predicted. Lee argues that predictability is the ability to anticipate the behavior of a system [38, 39, 40, 42]. A property of a model is predictable if there is a terminating procedure that proves that the property is a repeatable property of the model.

The predictability of the discrete dynamical systems is formally defined by measuring the deviation between the actual behavior and the predicted behavior [7]. The time predictability of a system is defined to be related to the difference between best case and lower bound on the one hand and upper bound and worst case on the other hand [53]. The former is called the best case predictability, and the latter is called the worst case predictability. The upper and lower bounds are usually computed off-line through, analysis, simulation, emulation and implementation, that, not during the run-time of the system. The predictability of a task is measured by the best case predictability and the worst case predictability. Kirner and Puschner analyze the possible explanations of the lack of a formal definition of predictability and gives a universal definition as the multiplication of analyzability with stability, including weighting factors [28]. The stability is given by the quotient of BCET over WCET of the time model. For WCET predictability the stability is ignored and the factor for it set to zero. The analyzability, which is now equal to the WCET predictability, as the quotient of WCET over

WCET bound. Henzinger argues that the programming model should not only be predictable in its function properties (what output does a program compute), but also predictable in its reaction properties (e.g., when does the program provide the output) and in its execution properties (e.g., what resources does the computation consume) [25]. He formalizes the notion of predictability as a form of determinism. An embedded system is time deterministic if, for every timed input stream, the timed output stream that is computed by the system is unique. He also emphasizes that the time determinism refers not only to the input and output values but also to the times at which input values are given to the system and the times at which output values are made available to the environment. No formal and quantifiable definition of predictability or determinism is given in this article.

Grund et al. propose the notion that predictability should capture if, and to what level of precision, a specified property of a system can be predicted by an optimal analysis [21]. They illustrate the proposition through the time predictability, which is defined as the quotient of BCET over WCET with all possible inputs and hardware states. To distinguish hardware- and software-related causes of unpredictability, they introduced the state-induced time predictability and input-induced time predictability by separately considering the sources of uncertainty. They only give the definition of time predictability, and treat the input to be the parameters of the time predictability. However, as we analyzed in Section 2.1, the input predictability is also important in CPS.

In summary, most of the state-of-the-art related researches regard the predictability as a continuum, and only take the predictability of the execution time of the function tasks into consideration. We agree with the idea of regarding the predictability as a continuum. However, we argue that the predictability of CPS should not be limited to the time predictability of function tasks. Both of the I/O behaviors and function task behaviors must be predictable, and both the time property and the order property must be predictable. And the execution time is not suitable to quantify the predictability for the concurrent and preemptive CPS. Therefore, in this paper, we illustrate the reason why the properties we propose must be predictable from different perspectives and define their predictability based on their major sources of uncertainties.

5. Summary and Future Work

CPS have to be predictable to ensure timeliness and improve the reliability of verification and composition. In spite of the great importance of the predictability, there is still no common agreements on the definition of predictability in CPS. The state-of-the-art definitions for predictability, which are studied in the conventional real-time system, are impractical and inadequate for the inherently concurrent and preemptive CPS. Therefore, we intend to propose metrics and definitions of predictability for CPS in this paper. We summarize the predictability requirements of CPS by analyzing characteristics of CPS and the I/O behaviors of typical programming models for CPS, and get the conclusion that both the task execution behavior and the I/O behavior must be predictable. Different from the state-of-the-art predictability definitions, which only consider the time predictability, we argue that the order property also must to be predictable. By analyzing the sources that lead to the uncertainties of the predictable properties, we propose different metrics to measure the predictability of those properties and present formalization of their definitions.

This paper introduces general definitions of predictability for CPS. However, the design and realization of CPS involve different levels of work, such as, design and model, programming and verification, runtime system and hardware support, etc. Therefore, the definitions proposed in this paper need to be optimized for different levels of work in the future. In addition, since our definitions covers new predictable properties, future work should also investigate the relation of them to other properties such as robustness, verification and compositionality.

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