Scheduling time-triggered tasks in multicore real-time systems: a machine learning approach

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***Abstract*—*Background*: Previous research and/or rationale for performing the study.**

***Aims*: Hypotheses/propositions to be tested, or goal of the study.**

***Method*: Description of the type of study, treatments, number and nature of experimental units (people, teams, algorithms, programs, tasks etc.), experimental design, outcome being measured.**

***Results*: Treatment outcome values, level of significance.**

***Conclusions*: Limitations of the study, implications of the results, and further work**

***Index Terms*—real-time system, scheduling, time-triggered tasks, DAG, multicore**

I. Introduction

Real-time systems are utilized in various domains such as air traffic control, public transportation, and automated vehicles. Unlike non-real-time systems, tasks in real-time systems must be both functionally correct and meet strict (or flexible) execution time constraints, known as deadlines. Failure to meet these deadlines can lead to severe consequences. The critical nature of these systems necessitates designing the system architecture with a focus on time and incorporating fault tolerance to ensure high reliability.

One example of such architecture is the time-triggered architecture (TTA) [1] [2], which offers a fault-tolerant communication protocol and a precise timing system to synchronize different electronic control units. Developing and running tasks on these architectures require in-depth knowledge of the system and its architecture, which complicates code reusability and scalability when adding hardware resources or upgrading to a larger system.

To address these issues, the Automotive Open System Architecture (AUTOSAR[1]) was developed. AUTOSAR introduces layers of abstraction between hardware, firmware, and software, enhancing software reusability and hardware scalability across different systems while maintaining safety and security standards. It is now the most widely used architecture among car manufacturers, with notable core partners including BMW, Ford, and Toyota.

Scalability, in particular, plays a crucial role in modern real-time systems. Increasingly, real-time systems such as autonomous cars or computer vision systems are enhancing their computational resources by transitioning to multiprocessor systems. This shift from uniprocessor to multiprocessor systems addresses the growing complexity and computational demands of tasks executed on these systems, aiming to reduce both the execution time of these tasks and the required resources [3].

Hence, an increasing number of real-time systems are utilizing multi-core hardware to parallelize their tasks and convert sequential programs into parallelized ones using frameworks such as OpenMP [2]. Unfortunately, in most real-life scenarios, the number of available processors/cores is fewer than the number of tasks/subtasks that can be executed in parallel (i.e., independent tasks). This means that not all independent tasks can be executed simultaneously on the system, raising the question: which task should be executed first?

This question is particularly important in a real-time context because having the wrong execution order, or schedule, could lead to, at best, a slow system, and at worst, deadline misses, which can have fatal repercussions. In the case of a self-driving car system, for instance, a slight delay of 500 ms in detecting a pedestrian crossing the road can, in some cases, be enough to drive over the pedestrian or cause a car accident. Note that the resources of real-time systems are scarce and limited, which is why using as little processing power as possible while ensuring that tasks meet their deadlines is of crucial importance.

The extreme case of this scheduling problem arises when only one processor is available to execute tasks. This is known as task scheduling on a uniprocessor, and [4] provided two major priority policies: Rate Monotonic (RM) and Earliest Deadline First (EDF) for scheduling periodic tasks. However, when considering multiple processors, the scheduling problem becomes much more complex, and different task models must be considered.

A prevalent task model is the time-triggered task model, which specifies tasks that execute periodically and is well-suited for time-triggered systems. Another type of task is the Logical Execution Time (LET) task. The LET paradigm is based on the time-triggered paradigm and was originally introduced by the Giotto real-time programming language [5] and later refined by [6] into the Hierarchical Timing Language

[1]https://www.autosar.org/

[2]OpenMP (2011) OpenMP Application Program Interface v3.1. http://www.openmp.org/mp-documents/OpenMP3.1.pdf

(HTL). The main principle behind the LET paradigm is that each task's inputs and outputs are read and written in zero time, i.e., constant time.

The benefits of using LET are twofold. Firstly, the zero-time communication semantics greatly improve the predictability of the overall system and make I/O operations (i.e., memory access) on shared resources deterministic, which is crucial in real-time systems due to the highly negative impact that memory access contentions can have on the system [7]. Secondly, using LET in programming also provides a layer of abstraction that facilitates the direct translation from modeling to implementation, thus ensuring the implementation of timing requirements, enhancing code maintenance, and producing a less error-prone code base [8].

One drawback of LET is its implementation overhead, which increases the execution times of tasks due to the zero-time communication semantics [9]. Despite this drawback, the advantages of LET make it attractive for real-time systems [10], which is why the focus here will be on time-triggered and LET task scheduling on multi-core systems. Given that the problem of scheduling independent tasks is NP-hard[3] [11], no scalable optimal algorithm exists. Therefore, heuristics are used to partially solve the problem.

Consequently, machine learning will be considered here as it can better approximate the unattainable perfect solution while being scalable in terms of computing time after the training phase. The research questions are:

RQ1 What is the current state-of-the-Art in scheduling event-chains of tasks ?

- RQ1.1 What is the current state-of-the-Art for DAG task scheduling ?
- RQ1.2 How has LET been used in scheduling event-chains ?
- RQ1.3 What machine learning techniques are used for DAG task scheduling ?

RQ2 Can machine learning be a better solution to schedule event-chains of tasks ?

- RQ2.1 Can a machine learning solution compare to state-of-the art heuristics for scheduling Directed Acyclic Graph tasks ?
- RQ2.2 Can a machine learning solution compare to ILP solutions while being more scalable ?

To achieve this, the background section will introduce various technical terms, concepts, and fundamental algorithms. Following this, a systematic literature review will be conducted to address R1, and finally, the artifact and experimental design, results, and conclusion will be presented to answer R2.

The solution we propose has the following features..
The primary contributions of this paper are:

II. Background

Task scheduling introduces several fundamental concepts.

[3]If a problem is NP-hard, it means that it is very unlikely to find a solution in polynomial time complexity, i.e., solutions are not scalable

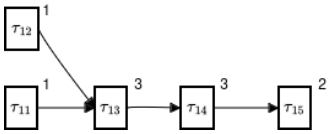

Fig. 1. DAG task τ_1. The nodes are the subtasks, the edges of the graph represent the precedence constraints between each subtasks and the worst-case execution time (wcet) of each subtask written as an exponent.

A. Periodic task and schedule

Firstly, a periodic task $\tau_i(C_i, D_i, T_i)$ is characterized by its worst-case execution time (wcet) C_i, its deadline D_i, and its period T_i. This definition can be expanded by including an initial offset, which corresponds to the time of the task's first execution, and an activation offset, which is the time delay between the task being ready to execute (i.e., its execution period has begun) and the task actually starting to run. Secondly, a schedule S is a function that assigns a boolean value for each task τ and each time tick t, indicating whether the task τ is running at time t. Therefore, a scheduling algorithm is the method that, given a set of tasks, produces a schedule S for the task set.

This task model and schedule definition are widely adopted in the literature (see section III) and are the building blocks of all scheduling algorithms. The periodic task model, in particular, is used to define more complex tasks such as DAG tasks (see below) that will be used as input in the machine learning model (see section IV).

B. DAG task

A Directed Acyclic Graph (DAG) task is a task that models the multiple subtasks of an chain of tasks that have a precedence constraints. For example, when considering the task τ_1 that makes an aircraft keep its altitude, you usually have a number of subtasks to handle this task, namely : reading from the altitude sensor (τ_{11}), reading for the speed sensor (τ_{12}), computing the new speed for the aircraft to keep its altitude (τ_13), computing the amount of thrust needed to achieve this new speed (τ_14), and finally actuating the aircraft's jet engine (τ_15). In this example, the DAG for τ_1 can be seen in Figure 1.

A DAG task τ_i also has a period T_i and a wcet C_i which is the sum of its subtasks wcets, and a deadline D_i. For instance, according to Figure 1, the wcet for τ_1 is 10 time units. You can also see how, for τ_1, the subtasks τ_{12} and τ_{11} can be parrallelized (i.e., executed in parallel) but the subtask τ_{13} needs to wait for both τ_{11} and τ_{12} to finish their execution before it can start running.

This concept will be the task model used in to conduct part of the systematic literature review (see Section III) and it also will be the task model used for designing the machine learning model (see Section IV).

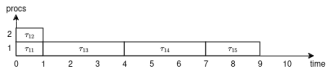

Fig. 2. Example of schedule for τ_1. The y axis represents the number of processors that are not idle. For the first two subtasks there are two processors active and for the rest there is only one active processor.

C. Utilization factor

The utilization factor represents the percentage of processing time that a taskset $(\tau_1, \cdots, \tau_n)$ will utilize. Formally, it is defined as

$$U = \sum_{k=1}^{n} \frac{C_k}{T_k} \tag{1}$$

where U is the utilization factor. This concept is significant because, when evaluating a scheduling algorithm S, we desire S to effectively schedule tasksets that maximize the utilization factor U. Consequently, the higher the utilization factor bound for S, the more efficient the scheduling algorithm. Additionally, this concept is valuable in real-time systems where processing resources are often limited and expensive, making it crucial to maximize their usage.

This concept is also used either as a measurement when comparing two scheduling algorithms and considering their utilization bound(see Section III), or used as a parameter to generate tasksets or DAG tasks with a fixed utilization (see Section IV).

D. Makespan

The makespan or end-to-end response time of a DAG task is the amount of time it takes for all the subtasks in the DAG task to finish executing when given a schedule. For instance, for the task τ_1 shown in Figure 1, the makespan of τ_1 for the schedule shown in Figure 2 is 9. Notice that in Figure 2, if the subtasks τ_{11} and τ_{12} were executed sequentially instead of in parrallel, the makespan would be one time unit longer, in this case 10 instead of 9.

This is a key measurement when dealing with DAG tasks (see Section III) and it will be the main efficacy criteria when comparing the machine learning model with state-of-the-art heuristics and ILP (see Section IV).

E. Capacity augmentation bound

Another measurement used when scheduling event-chains, or DAG, tasks is the capacity bounds, or capacity augmentation bound, which compares resource use to an theoretically optimal scheduling algorithm. It can also be used as a simple schedulability test. The matehmatical definition for a scheduling algorithm S of its capacity augmentation bound β is that, for any chain of events represented by a DAG G satisfying the following condition :

$$\beta \times U \leq m \wedge \beta \times len(G) \leq D, \tag{2}$$

the associated DAG is schedulable by S. Here, $len(G)$ is the length of the longest path, in terms of WCETs, in the graph G, D is the DAG task's deadline, m the number of processors and U is the utilization factor of the DAG task (with the WCET of the DAG being the sum of all tasks' WCET). As you can see, the lower β is, the better the scheduling algorithm.
This metric is used for DAG tasks or event-chains of tasks.

F. Optimality

A scheduling algorithm S is said to be optimal when the following condition is true: for every taskset Ω, if there exists a scheduling algorithm S' so that Ω is feasible by S', then Ω is also feasible by S. Where *feasible*, means that, using the schedule generated by S, all the tasks in the taskset will finish executing before their deadlines.

This concept is used in the literature, mainly for independent tasks scheduling (see Section III).

G. Acceptance ratio

When dealing with several independent DAG tasks or tasksets, the acceptance ratio is often used to measure the performance of a scheduling algorithm (see Section III). It consists of looking at a number of generated tasksets (or DAG tasks) and calculating the amount of schedulable (i.e., the schedule produced doesn't lead to a deadline miss) tasksets compared to the total amount of taskets. The resulting percentage is the acceptance ratio and the closer it gets to 100% for a scheduling algorithm, the better the scheduling algorithm.

This concept is also used as a metric, to assert the efficiency of scheduling algorithms when considering independent tasks (see Section III).

While the acceptance ratio, also called system schedulability, is used to measure the performance of scheduling alrogithms for independent tasks, the makespan and the capacity bound are only used for DAG tasks and tasksets representing chain of events.

H. RM and EDF scheduling

When designing a scheduling algorithm, the key decision involves determining which task should execute first when two or more independent tasks are ready to execute. This requires assigning each task a priority. [4] introduced two heuristics for this purpose: Rate Monotonic (RM) and Earliest Deadline First (EDF).

The RM algorithm is a fixed-priority scheduling algorithm, meaning that the priority of each task is known before execution begins. RM assigns the highest priority to tasks with the minimum execution rate, i.e., $\frac{C_k}{T_k}$, and is considered optimal for assigning fixed priorities to tasks. In contrast, EDF assigns priorities dynamically by selecting tasks based on which one has the earliest absolute deadline.

Figure 3 illustrates the difference between the two algorithms by scheduling the same two tasks, τ_1 and τ_2. τ_1 has a worst-case execution time of 0.5 time units and a period of 2 time units, while τ_2 has a worst-case execution time of 2 time units and a period of 3 time units. These are examples

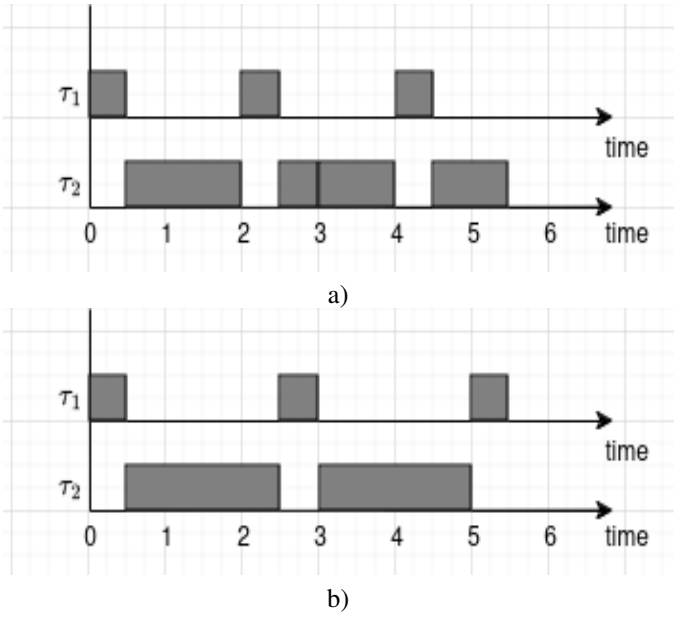

Fig. 3. Schedules of τ_1 and τ_2 using Rate Monotonic (a) and Earliest Deadline First (b) heuristics.

of implicit deadline tasks, where the relative deadline equals the end of their execution period.

Although EDF calculates each priority at runtime, it is optimal for uniprocessor scheduling and has a theoretical utilization bound of 1, which is the maximum possible for a feasible taskset on a single processor. RM, on the other hand, has a much lower utilization bound than EDF. While one might argue that RM introduces less runtime overhead and is therefore more practical, it has been shown that RM leads to more task preemptions (interrupting the execution of a task, as seen at times 2 and 4 for task τ_2 in Figure 3.a). This, combined with its lower utilization bound and non-optimality, makes EDF perform better than RM [12].

Although [4]'s work focused on uniprocessor systems, the proposed algorithms have also been applied to multi-processor scheduling. For example, Global EDF (GEDF) can be used on multi-core systems when allowing task migrations and Partitioned EDF (PEDF) is used when forbidding task migrations (The RM equivalents also exist).

III. Related Works

A. Systematic Literature Review process

This SLR aims at tackling RQ1. More precisely, the following research questions will be answered:

RQ1.1 What is the current state-of-the-Art for DAG task scheduling with precedence constraints ?

RQ1.2 How has LET been used in scheduling event-chains ?

RQ1.3 What machine learning techniques have been used for scheduling tasks on real-time systems ?

It will also be shown how the literature doesn't provide a complete answer to RQ2, hence the contributions of this paper.

From these research questions, several concepts have been isolated, namely, time-triggered tasks, the nature of the system (real-time multicore system), the scheduling of tasks, DAG tasks, and machine learning. The recording of the search results were done using the BibTeX LateX plugin combine with the google scholar "cite" feature.

Searching was conducted using the IEEE and ACM databases. According to the concepts identified above, the keyword chain used for searching was "("real-time" OR "real time") AND "system" AND ("time-triggered" OR "time triggered" OR "DAG" OR "Directed Acyclic Graph" OR "LET" OR "Logical Execution Time" OR "event chain" OR "event-chain") AND "task" AND ("scheduling" OR "scheduler" OR "schedule") AND ("multi-processors" OR "multi-cores" OR "multi processors" OR "multi cores" OR "multi-processor" OR "multi processor" OR "multi-core" OR "multi core")".

The search produced 3,549 results on the IEEE database which was reduced tp 1,171 papers when considering only articles published in the past 5 years.

Then the following exclusion criterias were used to filter out the rest of the articles, bringing the number of papers down to 19 (see Figure 4).

EC1 Not focusing on homogeneous multicores and hard RTS
"Heterogeneous" not in the title nor the abstract.
"mixed critical*" not in the title nor the abstract

EC2 Not focusing on scheduling
"scheduling" or "scheduler" or "schedule" in the title
"energy" not in the title
Focus on conference and journal papers

EC3 Not focusing on real-time systems, not proposing a scheduling algorithm, not using DAG, LET or event-chain tasks.

B. Findings of the Literature Review

In [13], authors use fluid scheduling to schedule multiple DAG tasks on a multicore system. Fluid scheduling has been used in previous work for independent time-triggered task scheduling [14] [15] but very few consider DAG tasks. Fluid-scheduling is known for producing optimal scheduling algorithms. Their method decomposes a DAG task into several sequential segments in which the subtasks will execute according to the fluid scheduling model. Although their algorithm significantly outperforms existing algorithms, the main limitation that is common to all fluid-based scheduling algorithm is the runtime overhead induced by the fluid-scheduling model. Although authors in [13] briefly explain how to transform their scheduling algorithm to a non-fluid one for practical implementation, they do not evaluate the overhead caused by the frequent task migrations and preemptions. Also, their algorithm only considers DAG task with implicit deadlines (D = T) which makes the response-time analysis simpler but to the cost of generalizability.

As a follow up, authors in [16] extend the fluid scheduling algorithm in [13] to constrained and arbitrary deadline tasks, especially focusing on DAG tasks with a deadline greater than

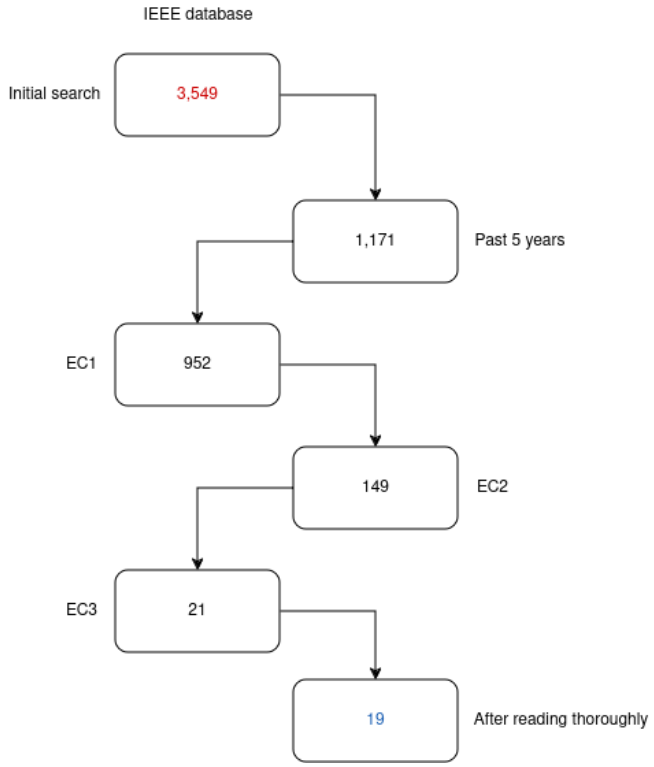

Fig. 4. SLR process diagram. EC stands for Exclusion Criteria, which are listed above.

their period. Their main contributions are their new scheduling algorithm that performs better than existing methods in terms of acceptance ratio, and producing the first theoretical capacity bound for DAG tasks with deadlines greater than their periods. However, the authors still don't provide any evaluation on the amount of runtime overhead their scheduling algorithm implementation produces which generally lowers the actual acceptance ratio of the algorithm.

Instead of considering fluid-scheduling, a popular scheduling method is federated scheduling. Federated scheduling is based on the idea of assigning heavy tasks ($U > 1$) to multiple cores for the whole duration of the tasks' executions, and assigning light tasks ($U \leq 1$) to execute on cores that have not been assigned a heavy task. Although it is popular, it suffers from a resource wasting problem, especially when the difference between the critical path's length and the deadline is small, which many papers aim at solving [17] [18] [19] [20] [21] [22].

[18], for instance, consider federated scheduling and GEDF and introduces a better metric called the util-tensity bound that extends the concept of capacity bound to have a better schedulability test. Based on this newly derived bound, the authors propose an extension to the classic federated algorithm, with very low tensity tasks being scheduled with GEDF, tasks with high-utilization and relatively high tensities are scheduled using the classic federated scheduling and low utilization tasks with relatively high tensities are scheduled using partitioned-EDF. Their algorithm, based on their newly derived bound, effectively improves the system schedulability of DAG tasks and reduces the resource wasting problem of federated scheduling. The main limitation of this paper is that they only consider GEDF for their util-tensity bound and also only consider implicit deadline DAG tasks.

This problem of resource wasting in federated scheduling is also tackled in [21] where the authors propose a federated and bundled-based scheduling algorithm which enhances the schedulability of DAG tasks compared to existing federated scheduling algorithms. Their method consists of using federated scheduling for tasks with high critical path to deadline ratio and bundled scheduling for tasks with low critical path to deadline ratio. Unfortunately, this paper only looks at 3 DAG tasks to evaluate their algorithm which is a really small amount and is not representative of the different DAG tasks that can exist.

Authors in [19] take another approach by proposing a virtually-federated scheduling algorithm that leverages the advantages of federated scheduling while improving the acceptance ratio for DAG tasks, outperforming existing algorithms. Their approach consists of adding a virtual layer of processors, on top of physical processors, and apply their federated-based scheduling algorithm on those virtual processors, thus enabling tasks to share a physical processor even though they are assigned to different virtual processors. The main drawback in [19] is that they only consider the heavy tasks (i.e., $U > 1$) and do not take the light tasks into account.

To fix this limitation, [20] extend their previous work [19] so that it considers both heavy and light tasks. The resulting virtually federated scheduling algorithm clearly outperforms any other federated-based scheduling algorithms in terms of acceptance ratio. However, they still only consider implicit or constrained deadline tasks and they don't provide any evaluation of the run time overhead their algorithm might induce.

[17] consider arbitrary deadline tasks and especially DAG tasks that have a deadline that is greater than their period. They introduce a new federated scheduling algorithm that takes those type of tasks into account and compare it to existing global or federated scheduling approaches for arbitrary deadline tasks, significantly outperforming most of them in terms of acceptance ratio. Their approach consists of using this new proposed aglgorithm for heavy tasks that have a deadline bigger than their period, then using classic federated scheduling for the heavy tasks with a constrained deadline, and finally using EDF-FF for the light tasks. Although the fluid-based method in [16] outperforms this new federated scheduling algorithm, the impracticality of fluid-based algorithm makes this algorithm the current best, in terms of acceptance ratio, for dealing with arbitrary deadlines. The main limitation of this work is that it doesn't tackle the resource wasting problem that classical federated scheduling, or their new algorithm, has or can potentially have, but only focuses on providing an algorithm for arbitrary deadline tasks.

For constrained deadline DAG tasks, [22] propose a

federated-based scheduling algorithm that outperforms on average by more than 18% previous SOTA [20] in terms of acceptance ratio, making this work the current SOTA for constrained deadline multi-DAG scheduling. Their approach uses the notion of degree of parallelism, which they define rigorously, to improve the classic federated scheduling way of choosing the number of cores to assign each heavy tasks. They also propose a new response-time bound for constrained deadline DAG tasks based on this defined notion. Although their method clearly stands out, they don't consider intra-task scheduling at all when their motivation came from the notion of degree of parallelism being used but wrongly defined in previous intra-task scheduling work [23] [24].

Federated scheduling isn't the only method used, [25], for instance, propose a decomposition-based approach to schedule multi-DAG tasks as well as a metric for testing the schedulability of tasks. Their decomposition strategy proves to be the most efficient , according to the defined metric, and the scheduling algorithm derived from it shows promising results in terms of acceptance ratio. Their decomposition strategy basically works by first definin execution segments and then then assigning subtasks to those segments using the laxity[4] of those subtasks so that no segments are overloaded with workload. The main limitation of this work is that they only look at GEDF variants for priority assignment and do not evaluate their decomposition method using other scheduling heuristics for multi-DAGs. Most of the articles presented up to now tackle inter-task scheduling, not considering the intra-task execution schedule.

Indeed, intra-task scheduling [26] [27] [28] [29] [30] [31] is often tackled as a separate problem due to the dependency constraints.

[27], for instance, introduce a scheduling algorithm , 'MAS', that shortens the makespan of periodic DAG tasks compared to the classic EDF dynamic priorty scheduling technique. Their algorithm is based on a clustering approach, combined with a technique called task duplication, and evaluate their results on an actual simulation object for real-time scheduling. Unfortunately, their evaluation is only based on a single DAG task and they only compare their algorithm with EDF. Their algorithm also shows a scalability problem compared to other existing algorithm with comparable results.

A scalable way of scheduling sub-tasks of a DAG is looking at priority-list scheduling which [26] use to propose an algorithm that effectively outperforms other intra-task DAG scheduling algorithms in terms of makespan. Their priority assignment algorithm is based on the length of the paths passing through each vertex. The longer the maximum length, the higher the priority. This effectively takes advantage of the inner graph structure to optimize the intra-task execution order, which is something that hasn't been done before this work. Although the authors compare their results with existing scheduling heuristics, they do not consider the, mathematically optimal, ILP method to compare their makespan results with the mathematically minimum makespan.

This priority-list scheduling approach is also used in [23] extend their previous work [24] which develop a priority assignment based on the critical-path execution first (CPEF) concept, effectively outperforming [26] in terms of makespan and providing a federated-based multi-DAG scheduling algorithm, compatible with this new priority-list scheduling algorithm. Their multi-DAG scheduling algorithms also outpeforms the multi-DAG algorithm used in [26]. Their method uses the vertices in the critical path as producers of workload for the parallelizable vertices to consume. For multi-DAG they look at assigning processors to DAG tasks, like in federated scheduling, using a parallelism-aware workload distribution model that uses their Concurrent Producer Consumer (CPC) model to assign cores while minimizing the inter-task workload interference. One limitation of their work is that, although they consider constrained deadlines for the response-time analysis, they only use implicit deadline DAG tasks for evaluating the system schedulability of their multi-DAG scheduling algorithm.

The priority-list algorithm proposed in [23] has been used for comparison in [30]. Indeed, authors in [30] design a deep reinforcement learning (DRL) model called GoSu which takes a DAG task as input and outputs a priority list of the DAG's subtasks. The makespan resulting from this priority-list is then compared to the results in [23] and [26] and the DRL model proposed in [30] outperforms them by up to 3%. The model is comprised of a graph convolutional network layer to encode the graph structure information, and a sequential decoder layer based on the attention-mechanism, which produces a priority list of the vertices. The reinforcement learning uses the makespan as the reward to minimize and the REINFORCE algorithm is used to find the best policy. Although the time it takes for the model to run is measured, no comparison with the ILP method is done and there is no evaluation of the scalability of the model when increasing the amount of cores in the system or the amount of subtasks in a DAG task. But [30] isn't the only work considering DRL as a method for DAG intra-task scheduling.

Indeed, [29] also use the DRL approach to tackle the intra-task scheduling problem and compare their results to the makespan obtained by solving the equivalent ILP problem. Their model achieves up to 75% of makespan reduction compared to ILP, that is, the makespan produced by the ILP method is 25% smaller than the makespan produced by their DRL model, which is a relatively good performance as the ILP approach gives the mathematically minimum makespan. The more important result, however, is that when you increase the subtasks in the DAG tasks, the ILP method explodes in terms of computing time when the DRL approach gives a result in a relativley short time, making it scalable, unlike ILP. The model uses a combination of a graph neural network with attention layers to better capture the structure and dependency information of the DAG task. The makespan

[4]Laxity is the gap between the total execution time of a task (potentially comprising the I/O delays) and its deadline.

is also used for the reward function but Soft Actor Critic algorithm is used for training the model. Unfortunately, the paper doesn't provide an evaluation when increasing the number of cores in the system and also doesn't compare their model to SOTA heuristics, which also aim to approximate the optimal solution given by the ILP method.

Those intra-task scheduling papers only consider the theoretical makespan when task migration and preemption is instantanious, but they don't take the runtime overhead into account. One major factor in the runtime overhead is the communication delays between each subtasks of a DAG task, which are rarely considered. To that end, [28] propose an extension of the DAG task model to add execution groups that bind groups of subtasks to a single physical core, thus reducing inter-core communication which can cause major communication delays depending on the topolgy of the system. They also introduce a scheduling algorithm and compare the makespan of their approach to existing methods such as federated scheduling and critical path-based scheduling. Their method shows comparable results while minimizing the communication overheads. However, the evaluation is only done on 100 generated DAG tasks which is a small sample size compared to the other papers [23] [26]. Also, although they introduce a way to extend their approach to schedule multiple DAGs, they do not provide any evaluation of that.

[31] takes it further by looking at the real-time simulation system FRTDS and using the I/O usage and ram allocation to construct a cost function, which is then used as a reward for their proposed DRL model to schedule DAG's subtasks. The cost is divided into a current cost, what we know, and the future cost which is predicted using the subtask's successors. The model performs better, in terms of makespan, than existing scheduling algorithms implemented on the FRTDS platform but because of the RL process accumulating the previous subtask's execution as experience to learn, the method uses a lot of memory which affects the speed of execution.

Other than delays, communication, especially inter-core communication, can lead to non-determinism when wrongly implemented, which violates the safety rules of hard real-time systems. As a consequence, the Logical Execution Time has been introduced in the early 2000s [5]. Unfortunately, LET implementations can suffer from contention problem as well as overheads which increases the WCET of regular DAG tasks when executed on the system.

As such, [32] propose a LET DAG task scheduling algorithm that avoids contentions using a heuristic, while reducing the runtime overhead caused by the LET semantics implementation. Their approach is based on a minimum laxity-first priority assignment algorithm for scheduling the subtasks of the DAG task and multi-DAG scheduling is done using each task's job's earliest start time (EST) and earliest finish time (EFT) to avoid communication contentions between jobs. Their method considerably reduces the makespan compared to LET tasks being scheduled without avoiding contentions and the deadline-miss ratio when scheduling multiple jobs is also significantly lowered. Although they use a multiple-cluster, multicore architecture to perform the experiment, they only consider one cluster and don't extend their approach to scheduling tasks on multiple-cluster.

Another approach at minimizing the inter-core communication delays is using the Direct Memory Access (DMA) protocol which transfer data from one core to another, without using local buffers. Indeed, typical implementations of LET use local buffers in every core of the system which read/write data from/to a global memory. This mechanism can be coslty when dealing with huge amounts of sensor data, such as in autonomous driving systems. Hence, [33] propose a DMA-based protocol to handle LET communications semantics on multi-core systems that minimizes the read/write latency of each task. They do so by having an LET task on each core being responsible for programming the DMA engine so that the LET communications can happen. They also introduce a scheduling algorithm for the communication tasks, based on mixed-ILP (MILP) problem formulation, minimizing either the number of DMA data communications or the maximum communication delay to period ratio of each task. Their MILP method produces an optimal schedule and improves by up to 98% the communication delays compared to the classic Giotto approach of LET [5]. Unfortunately, they do not consider the scalability, in terms of the number of subtasks per DAG tasks, of their method and they do not provide any evaluation of their method applied to existing DAG scheduling algorithms to see how their LET protocol impacts the acceptance ratio of those scheduling algorithms.

Table I gives a summary of the findings.

According to these findings, the current state-of-the-Art for DAG task scheduling (RQ1.1) seems to be a federated-based scheduling approach for inter-task scheduling and a global priority-list approach for intra-task scheduling [22] [23]. Although those papers don't consider communication overheads which is where LET (RQ1.2) is moslty used when looking at scheduling LET tasks, to reduce the amount of overhead so that the LET interval of a task can be as close to its wcet as possible while respecting the advantageous LET semantics.

In terms of machine learning techniques (RQ1.3), every article found uses deep reinforcement learning for scheduling DAG tasks. More specifically, the model proposed is often a combination of a kind of graph neural network and attention layers to produce a priority-list of the subtasks of the DAG task.

Multiple limitations were found for each paper. Notably, the type of task that is considered which mostly is constrained or implicit deadline tasks and arbitrary is rarely considered due to the complexity it adds to the scheduling analysis. Also, there hasn't been any use of supervise machine learning for real-time task scheduling and only one paper looked at comparing a machine learning solution to the optimal schedule provided by the ILP methodology.

IV. Research Methodology

Reference	Scheduling technique	Task type	Relevancy
[13]	fluid	implicit deadline	RQ1.1
[26]	priority-list	constrained deadline	RQ1.1
[21]	federated and bundled-based	constrained deadline	RQ1.1
[27]	clustering	constrained deadline	RQ1.1
[32]	priority-list	LET constrained deadline	RQ1.1, RQ1.2
[18]	federated and GEDF and PEDF	implicit deadline	RQ1.1
[25]	Decomposition-based	implicit deadline	RQ1.1
[22] [19] [20]	federated-based	constrained deadlines	RQ1.1
[28]	partitioned / clustering	constrained deadlines	RQ1.1
[17]	federated	arbitrary deadline	RQ1.1
[29] [30] [31]	DRL	constrained deadline	RQ1.1, RQ1.3
[34]	DRL	non-DAG implicit deadline	RQ1.3
[23]	priority-list and federated	constrained deadline	RQ1.1
[16]	fluid	arbitrary deadline	RQ1.1
[33]	Mixed ILP	LET, constrained deadline	RQ1.1, RQ1.2

TABLE I
SLR SUMMARY TABLE

This research could have been conducted using alternative methodologies. Provide a summary of the best fit methodologies, and their relative strengths and weaknesses (max 2-3 paras).

The "name of methodology" was chosen to conduct this research. Give details about how this methodology was adapted for your project (max 2-3 paras).

Include a clear plan with objectives and outcomes (gantt chart)

V. Contribution 1

Oh by the way, [**?**] did some great work.
Give an overall summary of the steps involved.

VI. Contribution 2

Give an overall summary of the steps involved.

VII. Experimental Results

Set up: what experiments/benchmarks were chosen?
Execution of results: how were the experiments conducted
Data: what was found to have happened?
Synthesis: what does the data mean?
Relevance: how does this work compare to others, and to what extent does it answer the RQs
Limitations:

VIII. Conclusions and Future Works

Acknowledgement

For referencing in LaTeX, check out: https://texblog.org/2014/04/22/using-google-scholar-to-download-bibtex-citations/

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