

A CONTROL-THEORETICAL METHODOLOGY FOR THE SCHEDULING PROBLEM

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Abstract

This paper presents a novel methodology to develop scheduling algorithms. The scheduling problem is phrased as a control problem, and control-theoretical techniques are used to design a scheduling algorithm that meets specific requirements. Unlike most approaches to feedback scheduling, where a controller integrates a “basic” scheduling algorithm and dynamically tunes its parameters and hence its performances, our methodology essentially reduces the design of a scheduling algorithm to the synthesis of a controller that closes the feedback loop. This approach allows the re-use of control-theoretical techniques to design efficient scheduling algorithms; it frames and solves the scheduling problem in a general setting; and it can naturally tackle certain peculiar requirements such as robustness and dynamic performance tuning. A few experiments demonstrate the feasibility of the approach on a real-time benchmark.

1 Introduction

The word *scheduling* refers to the allocation of resources between different competing tasks. This generic, abstract definition reflects the pervasiveness of the scheduling concern across disciplinary fields. A concrete class of scheduling problems is obtained by specifying a type of system and tasks, and the goals of the scheduling action.

In this paper, we outline a general methodology to tackle the scheduling problem. Our approach exploits *control theory* to formulate the scheduling problem and to solve it. The control-theoretical paradigm represents the interaction between two distinct parts of a system: the *plant* and the *controller*. The plant represents the part of the system whose dynamics is not modifiable directly, and that must be put under control. The controller, on the other hand, is a component that provides suitable input to the plant with the goal of influencing its dynamics towards meeting some requirements. The controller chooses its action according to the output of the plant, hence the denomination *feedback control*.

The idea of using control theory to solve scheduling problems is not new. Indeed, the research area of *feedback scheduling* is based on these premises [11, 5]. The novelty of our approach consists in how the control-theoretical paradigm is applied to the scheduling problem, and more precisely which parts of the system are modeled as the plant and as the controller, respectively.

The most common approach to feedback scheduling supplements an existing scheduler with a control-theoretical model: the plant is the “basic” scheduler

itself, and the controller tunes its dynamics over time according to the evolution of the rest of the system. We suggest a different partitioning, where the controller *is* the scheduler and the plant is a very abstract model of the pool of tasks and, in some sense, the resources they run on.

Our stance has a couple of significant advantages over the traditional approaches. First, it allows the effective re-use of an extensive amount of powerful results from classical control theory to smoothly design scheduling algorithms. Second, it is remarkably flexible and can easily accommodate some complex and peculiar scheduling requirements, such as robustness towards disturbances, dynamic adjustment of performance, and a quantitative notion of convergence rates.

The approach is general and applies to a large class of scheduling problems. It is naturally applicable to scheduling the CPU in *real-time systems* [14, 8], which are characterized by a quantitative treating of time. As it is common with feedback scheduling, it focuses on *soft* real-time, where the failure to respect a deadline does not result in a global failure of the system, and average performance is what matters.

The heterogeneous scope of the scheduling problem and the sought generality of the present approach make, at times, the presentation of the technical details necessarily abstract: it is impossible to formalize each and every (domain-specific) aspect of the scheduling problem (e.g., deadlines, priorities, granularities, etc.) in a unique model that is practically useful. Additionally, different formalizations are often possible, and choosing the best one depends largely on application-specific details, such as whether one is dealing with a batch or a hard real-time system. The overall goal of the present paper is high-level: outlining the framework proposed, formalizing its basic traits, and demonstrating its flexibility with a few examples. Focusing the framework on specialized classes of scheduling problems and comparatively assessing its performance belongs to future work.

The rest of the paper presents our approach to feedback scheduling and is organized as follows. Section 2 presents some additional motivation, with a more direct comparison to the literature which is most closely related to this paper. Section 3 introduces our methodology for the scheduling problem; it focuses on presenting the conceptual contribution in a general setting. Section 4 discusses an experimental validation of the approach, where the general methodology is instantiated to solve a few specific concrete problems in a real-time scheduling benchmark. Finally, Section 5 draws some conclusions and outlines future work.

2 Motivation and related work

Hellerstein et al.'s book [4] is a comprehensive review of the applications of control theory to computing-system problems such as bandwidth allocation and unpredictable data traffic management. In general, control theory is applied to make computing systems adaptive, more robust, and stable. Adaptability, in particular, characterizes the response required in applications whose operating conditions change rapidly and unpredictably.

Lu et al. [9, 10] present contributions in this context, for the regulation of the service levels of a web server. The variable to be controlled is the delay between the arrival time of a request and the time it starts being processed. The goal is

to keep this delay to within some desired range; the range depends on the class of each request. An interesting point of this work is the distinction between the transient and steady state performances, in the presence of variable traffic. This feature motivates a feedback-control approach to many computing-system performance problems.

Scheduling is certainly one of these problems where the transient to steady-state distinction features strongly. Indeed, many *ad hoc* scheduling approaches solve essentially the same problem in different operating conditions. This is one of the main reasons why *feedback scheduling* has received much attention in recent years (see Xia and Sun [19] for a concise review of the topic). As we argued already in the introduction, the standard approach in feedback scheduling consists in “closing some control loop around an existing scheduler” to adjust its parameters to the varying load conditions. This may yield performance improvements, but it falls short of fully exploiting the rich toolset of control theory.

For example, in Abeni et al. [1], the controller adjusts the reservation time (i.e., the time the scheduler assigns to each task) with the purpose of keeping the system utilization below a specified upper bound. The plant is instead a switching system with two different states, according to whether the system can satisfy the total amount of CPU requests or not. Some tests with a real-time Linux kernel show that the adaptation mechanism proposed is useful for to improve quality-of-service measurements. Continuing in the same line of work, Palopoli and Abeni [12] combine a reservation-based scheduler and a feedback-based adaptation mechanism to identify the best parameter set for a given workload. Block et al. pursue a similar approach [2] where they integrate feedback models with optimization techniques.

In Lawrence et al. [7], the controller adjusts the reservation time to within an upper bound given by the most frequently activated task. The model of the plant is a continuous-time system whose variables record the queuing time of tasks. The effectiveness of the method proposed is validated through simulations.

Lu et al. in [11] consider some basic scheduling policies (both open-loop and closed-loop) and design a controller that prevents system overloading. Such goal is achieved by letting some tasks out of the queue when the system workload is too high.

All these approaches target the same problem: assigning CPU time to a pool of tasks to meet some goals. The devised algorithms are usually extremely efficient, but their scope of applicability is often limited to a fairly specific domain (e.g., periodic processes with harmonic frequencies deadlines). Moreover, in all the cited approaches the controller modifies the behavior of a “basic” scheduling algorithm; indeed, the model of the scheduler is often combined with (some aspects) of the processor model, even if their functions are in principle clearly distinct. We believe that this lack of separation of concerns is the result of the close adherence to a specific scheduling problem domain, and we claim that enforcing a stricter separation in the model can result in some distinctive advantage.

The rest of the paper presents an approach where the scheduler is solely responsible for selecting which tasks have to run and their desired execution time. The scheduler is then built as the controller that meets some requirements for such a selection. Notice that the homogeneous nature of the controller (i.e., the scheduler) and the plant (i.e., the tasks’ execution model) is peculiar to com-

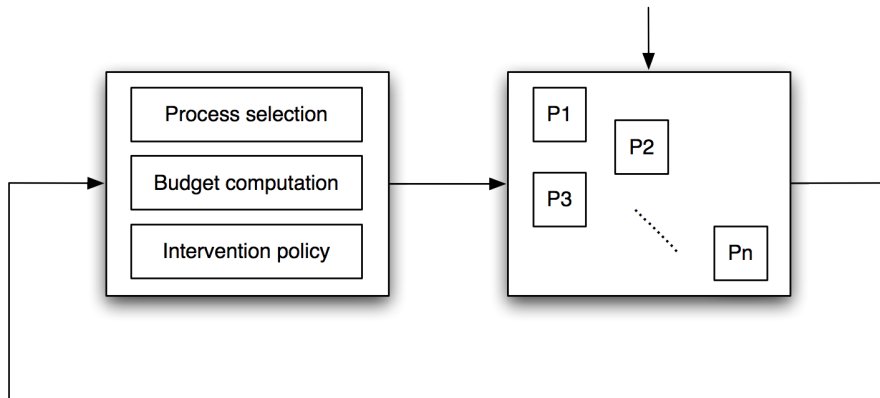


Figure 1: The general framework proposed.

puter systems, and makes a unitary design of the overall system easier. The approach itself can be, we believe, more general and flexible than the aforementioned others.

3 The methodology

This section outlines a methodology to tackle the scheduling problem. For clarity, it is phrased in terms of allocating CPU time to a set of tasks in a mono-processor operating system. It should be clear, however, that the solution refers to a more abstract class of problems and is relatively general. In the rest of the paper, we assume familiarity with the basic control-theoretical terminology and notation (see e.g., [4]).

The basic modeling assumption completely separates the processor and the scheduler: the scheduler chooses the order in which the tasks are executed and their execution times, while the processor actually runs them. This separation let us focus more precisely on the characteristics of each component and understand how to change each model according to the requirements we have to meet. Figure 1 shows the “big picture” of how the scheduling problem is cast as a control problem.

The processor is a system that executes tasks according to the input received from the scheduler. The scheduler, which provides this input, is then the controller of the processor, which is the plant. The control action is divided in three aspects: task selection, budget computation, and choice of the intervention policy. The first two phases choose which tasks will be executed, in what order, and the budget — defined as the maximum running time before preemption — assigned to each of them.

The intervention policy, instead, determines when the scheduler will next be activated. In the following, we assume a straightforward intervention policy where the scheduler runs after every scheduling round. More complex policies can of course be introduced according to the requirements of specific applications; for example, the scheduler might run whenever the difference between the desired execution time and the real measured time exceeds a certain threshold.

A detailed analysis of this aspect is orthogonal to the rest of our methodology and belongs to future work.

Separating the scheduler action in three components facilitates modifications of the controller model according to different requirements. More precisely, the overall model structure remains the same and only the equations modeling the affected aspects need to be changed.

Notice that anything that influences the behavior of the running tasks, other than the scheduler action, is modeled as an exogenous disturbance: an action that prevents the system from reaching the goal requirements, which the scheduler wants to contrast. This modeling assumption is suitable for factors that are, for all practical purposes, unpredictable and unmodifiable. The notion of disturbance (basically disturbance rejection) from control theory is then adopted to model these factors, with the immediate benefit of having at our disposal a powerful set of theoretical tools to tackle effectively the ensuing problems.

The abstractness and genericity of our framework come with the potential drawback of making it difficult to implement the scheduling policies within an existing scheduler architecture, which can differ significantly from the abstract modular structure of Figure 1. Anyway, we believe that the theoretical analysis that can be carried out within our framework is extremely useful to determine the criticalities of the system under design, even in the cases in which the final implementation will require *ad hoc* adjustments.

3.1 The plant

The “open loop” model of the plant describes the process executor as a discrete-time system. It receives a schedule (which will be the output of the scheduler described in the next subsection) as input and returns the outcome of executing the tasks as required by the schedule.

A *round* is the time between two consecutive runs of the scheduler. Assume that more than one task can be scheduled for execution in a given round; correspondingly, we introduce the following variables to describe the plant:

- N , the number of tasks to be scheduled;
- $\tau_p(k) \in \mathbb{R}^N$, the actual running times of the tasks in the k -th scheduling round;
- $\tau_r(k) \in \mathbb{R}$, the duration of the k -th round;
- $s(k) \in \mathbb{R}^N$, the schedule at the k -th round: an ordered list of the budgets, one for each task; the order determines the execution order and a budget of 0 means that the task is not scheduled for execution in that round;
- $\delta b(k) \in \mathbb{R}^N$, the disturbance during the k -th round, defined as the difference between the assigned budget and the actual running time of a task; (Notice that this variable models uniformly a variety of possible specific phenomena, such as a task that yields control or terminates before preemption, an interrupt occurring, the execution of a critical section where preemption was disabled, etc.)
- $t \in \mathbb{R}$, the total time actually elapsed from the system initialization.

The model of the plant is then the following system of equations:

$$\begin{cases} \tau_p(k) &= s(k-1) + \delta b(k-1) \\ \tau_r(k) &= r_1 \tau_p(k-1) \\ t(k) &= t(k-1) + \tau_r(k-1) \end{cases} \quad (1)$$

where r_1 is a row vector of length N with all unit elements.

Model (1) is linear and time-invariant. Negative budgets are not allowed and, correspondingly, each $s(k) + \delta b(k)$ element cannot be negative. However, this is irrelevant for the controller, since the set of considered variables is smaller than the domain limitations. Notice that the discrete-time model assumes that the scheduler is active only once per round. Clearly, some $s(k)$ elements can be zero, meaning that not all the tasks will actually run. The τ_r variable models round duration, which takes into account system responsiveness issues.

3.2 The scheduler

A scheduler should usually achieve the following goals, regardless of the specificities of the system where it runs [16].

- *Fairness*: comparable tasks should get comparable service; (This obviously does not apply to tasks with different properties.)
- *Policy enforcement*: the scheduler has to comply to general system policies; (This aspect is especially relevant for real-time systems where constraining system policies are usually in place.)
- *Balance*: all the components of the system need to be used as uniformly as possible.

In addition to these general requirements, a scheduler must also achieve additional goals that are specific to the system at hand. For instance, in batch systems, where responsiveness is not an issue, the scheduler should guarantee maximization of the throughput, minimization of the turnaround time, and maximization of CPU utilization. In interactive systems, on the contrary, minimization of response time and proportionality guarantees are likely scheduling goals. Finally, deadlines and predictability are specific to real-time systems.

In the following, we outline a general approach to design a scheduler — based on control-theory and the framework presented above — that achieves a defined set of goals. Unlike the standard approach that designs a new algorithm for a new class of systems, we can accommodate most scenarios within the same framework by changing details of the equations describing the control model.

Process selection and budget computation. The scheduler decides which tasks to activate and chooses a budget for them. This is achieved by setting variable $s_i(k)$ which defines the budget assigned to the i -th task at round k . This action is actually made of two conceptually different parts. A Process Selection Component (PSC) takes care of deciding the next task to be executed by the processor, while a Budget Computation Component (BCC) fixes the duration of the execution for each selected task. If more than one task is to be executed per round, PSC computes an ordered list of tasks and BCC assigns one or more budgets to the elements of the list. Execution need not be

continuous: if a time \hat{t}_i is assigned to the i -th task, the actual execution can be split into multiple slots within the same round.

The distinction between PSC and BCC is modeled by defining $s(k)$ as $S_\sigma(k) b(k)$, where $S_\sigma(k)$ is a $N \times n(k)$ matrix representing the tasks selected at the k -th round, while $b(k) \in \mathbb{R}^{n(k)}$ represents the budget assigned to the selected tasks. Notice that, in the most general case, the number of tasks that can be executed at each round is a variable $n(k)$.

PSC can operate statically or dynamically. In the first case, the strategy is independent of the previous choices, such as in Round Robin (RR) scheduling. In the second case, PSC retains a history of the previous choices and bases its new choice on it, such as in fair-share scheduling [6].

In case of static PSC, the matrix $S_\sigma(k)$ is not explicitly function of $b(i)$ and $S_\sigma(j)$, with $i, j < k$. This means that $S_\sigma(k)$ may not be a function of both τ_p and τ_r in the previous rounds; indeed, these represent the actual behavior of the CPU with respect to each task. Therefore, they may not reflect the choice that the scheduler made in previous rounds, due to contingencies in the execution of the system. Consider, as a more concrete example, the shortest remaining time next algorithm: the PSC chooses the next task to be executed according to their remaining running times, which obviously depend on what actually happened in the previous rounds (i.e., the history of τ_p), but not necessarily on the scheduler's choice (i.e., s).

Once the PSC has selected the tasks to be executed, the BCC computes the budgets for them, by setting $b(k)$. PSC can be static or dynamic, too: in the first case the budget is a constant vector $b(k) = \hat{b}$, whereas in the second case the budget may change at every round.

Designing the controller. Let us now discuss how to define and enforce some of the previously outlined features in a scheduler, for given PSC and BCC.

3.2.1 Fairness

A fair scheduling algorithm has the property that, in every fixed time interval, the CPU usage is proportionally distributed among tasks, accordingly to their weights. For the sake of simplicity, let us focus on a fixed number of rounds H .¹ Let $p_i(k)$ be the weight of the i -th task at the k -th round. In order to guarantee fairness for each task, the scheduler must achieve the following equation:

$$\sum_{i=k}^{k+H} \tau_{p_i(k)} = \sum_{i=k}^{k+H} \frac{p_i(k)}{\sum_{j=1}^N p_j(k)} \tau_r(k) \quad (2)$$

Informally, (2) means that the scheduler distributes the CPU among the different tasks proportionally to their weights (over the next H rounds). Then, the scheduler computes a $s(k)$ which satisfies equation (2). The algorithm to compute $s(k)$ comes from the solution to the corresponding control problem, for example by means of optimal control theory²: find the optimal value of the controlled variable $s(k)$, given a certain cost function J of the state variables τ_p, τ_r, t .

¹Generalizing this approach to deal with a time window, rather than a number of rounds, is straightforward.

²See [3] for an overview of optimal control theory and further references on the subject.

3.2.2 Policy enforcement

The details of how to handle this aspect within our control framework depend essentially on *which* system policy should be enforced: the term “policy” can refer to very disparate concerns. The experiments described in Section 4 will tackle a specific instance of activation policy.

Let us notice, in passing, that the strict coupling between the system policy and the features of the controller that enforce such a policy is one of the reasons why most scheduling algorithms do not disentangle the different aspects and tend to lump all of them together in the same model.

3.2.3 Balance

Balance requirements do not belong to the simplified model of equation (1), which refers to a mono-processor system whose only resource is CPU time. It is straightforward, however, to extend the model along the same lines to accommodate additional resources, such as another CPU or I/O bandwidth. New variables would model the usage of these further resources, with the same assumptions as in (1). Of course, these control variables must be measurable in the real system for the scheduler to be effectively implementable (see [5] for a discussion of this orthogonal aspect). Then, control-theoretical techniques — such as optimal control theory or model-predictive control — can be used to design a scheduler which enforces a resource occupation given as a set point.

3.2.4 Throughput maximization

If throughput is part of the requirements for our scheduler, we include the following set of equations in the model (1):

$$\rho_p(k) = \max(\rho_p(k-1) - \tau_p(k-1), 0) \quad (3)$$

Equation (3) defines $\rho_p(k)$, the remaining execution time of task p at round k , as the difference between the remaining time during the previous round and the actual running time of p during the current round. Throughput maximization can then be defined as the round-wise maximization of the number of processes whose ρ_p value is zero. Standard control-theoretical techniques can then design a controller that provably achieves this requirement.

3.2.5 Responsiveness

The model (1) includes a variable τ_r that describes the duration of a round, hence requirements on the response time can be expressed as a target value for τ_r . More precisely, the smaller τ_r , the more responsive is the controlled system.

3.2.6 Other requirements

The same framework can address other requirements, such as turnaround time, CPU utilization, predictability, proportionality, and deadline enforcement. As an example, the experiments in Section 4 will address proportionality and deadline enforcement explicitly.

3.3 Complexity parameters

Analyzing the complexity of scheduling algorithms is often arduous, mostly due to the difficulty of determining the right level of abstraction to describe the various components (i.e., the processor, the scheduler, etc.). It also does not make sense to compare directly the general framework we have outlined to existing algorithms; on the contrary, specific implementations can be experimentally evaluated.

It is nonetheless interesting to present a few simple rules of thumb to have a rough estimate of the complexity of an algorithm designed within our framework. With the goal of determining the number of elementary operations spent by the CPU to execute the scheduling algorithm itself, let us introduce the constants t_Σ , t_S , t_Π , and t_\rightarrow . They denote the (average) duration of a sum, subtraction, multiplication, and bit-shift operation, respectively. Also, let t_c denote the (average) duration of a “light” context switch (i.e, the time overhead taken by operations such as storing and restoring context information, which does not include the actual computation of the next task to be run and its budget). Using these figures, Section 4 evaluates the complexity of a specific algorithm that validates our framework.

4 Application and experimental results

This section instantiates the framework proposed by developing a scheduler with certain proportionality and deadline meeting requirements with control-theoretic techniques. The design is evaluated on the Hartstone [18, 17] benchmark, a standard real-time system benchmark. The Hartstone benchmark evaluates deadline misses and was initially conceived to assess architectures and compilers, but it can be used also for evaluating the performances of a scheduling algorithm.

The design and the evaluation are necessarily preliminary, and do not tackle every aspect that is relevant in real-time scheduling (for example, earliness/tardiness bounds are not considered); these experiments are meant as a feasibility demonstration of the approach and tackling more challenging problems belongs to future work.

Regulating round duration and CPU distribution. One of the requirements fixes a desired duration for scheduling rounds; let τ_r° denote such a duration. Moreover, define

$$\theta_p^\circ \in \mathbb{R}^N, \quad \theta_{p,i}^\circ \geq 0, \quad \sum_{i=1}^N \theta_{p,i}^\circ = 1 \quad (4)$$

as the vector with the *fractions* of CPU time to be allotted to each task. This vector can be expressed as a function of workload and round duration, and the corresponding requirement be expressed as a set point for each task. More generally, notice that requirements on fairness, tardiness, and similar features, are also expressible in terms of τ_r° and θ_p° .

Let us now show a possible approach to design a scheduler that meets the requirement on the duration of the scheduling rounds. Consider for example a cascade controller such as in Figure 2. An appropriate choice for the involved

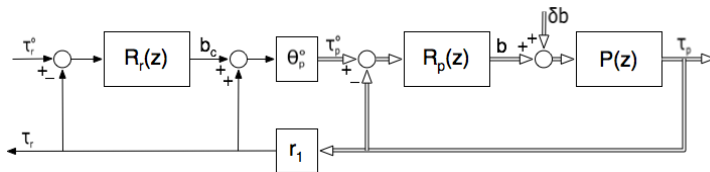


Figure 2: The control scheme proposed.

regulators is to give R_r a PI structure:

$$R_r(z) = k_{rr} \frac{z - z_{rr}}{z - 1} \quad (5)$$

while selecting R_p as a diagonal integral regulator with gain k_{pi} :

$$\begin{aligned} A_{R_p} &= I_N, & B_{R_p} &= k_{pi} I_N, \\ C_{R_p} &= I_N, & D_{R_p} &= 0_{N \times N}. \end{aligned} \quad (6)$$

Correspondingly, one can perform a model-free synthesis getting the values $k_{rr} = 1.4$, $z_{rr} = 0.88$, and $k_{pi} = 0.25$. These values instantiate a cascade controller which we take as our BCC. For the PSC, let us choose a simple approach where every task with a positive computed budget is activated following a Round Robin policy.

Benchmark description. The Hartstone benchmark defines various series of tests. Each of them starts from a baseline system, verifies its correct behavior, and then iteratively adds workload and re-verifies its correct behavior until a failure occurs. The final amount of (supported) additional workload gives a measure the system performance. For brevity (and without loss of generality), we consider only the first series of the Hartstone benchmark — the “PH series”, which deals with periodic tasks — in this paper. The PH (Periodic tasks, Harmonic frequencies) series adds tasks and modifies their period and workload to stress the system. Tasks are periodic and harmonic.

The baseline system [18] consists of five periodic tasks. Each task has a frequency and a workload. All frequencies are an integral multiple of the smallest, and the workload is determined by a fixed amount of work to be completed within the task’s period. More precisely, each task has to execute a given number of “Wheatstones” within a period, hence the workload rate is measured in Kilo-Whets instruction per second [KWIPS]. In our tests, we assume that the CPU can complete 1 KWIPS in 25 time units. We do not change this figure throughout our simulations, thus neglecting the overhead on the hardware of executing the scheduler. In addition, let a frequency of 1 Hertz correspond to a period of 20000 time units. All the tasks are independent: their execution does not need synchronization and they are all scheduled to start at the same time. The deadline for the workload completion for each task coincides with the beginning of the next period. These assumptions are appropriate, for example, for programs that monitor several sensors at different rates, and display the results without user intervention or interrupts. Table 1 gives details on the baseline system.

Benchmark evaluation. We run the benchmark with three different algorithms: the one regulating CPU distribution and round duration (designed

Task	Frequency	Workload	Workload rate
1	2 Hertz	32 Kilo-Whets	64 KWIPS
2	4 Hertz	16 Kilo-Whets	64 KWIPS
3	8 Hertz	8 Kilo-Whets	64 KWIPS
4	16 Hertz	4 Kilo-Whets	64 KWIPS
5	32 Hertz	2 Kilo-Whets	64 KWIPS

Table 1: The baseline task set.

above within our framework) with three different values for τ_r° , as well as the standard (real-time) policies EDF and LLF. The yardstick for the evaluation is a simple Round Robin scheduler.

The presented results used the Scilab environment [13] to perform the simulations; this allowed a high-level evaluation of the scheduling algorithms that is not tied down to any lower-level implementation detail. As a further validation, we also run the same tests within the Cheddar framework [15]. The results of the two sets of tests, with Cheddar and with Scilab, essentially coincide, therefore reinforcing our confidence in the soundness of the evaluation.

In the first PH test, the highest-frequency task (task 5) has the frequency increased by 8 Hertz at each iteration, until a deadline is missed. This tests the interactivity of the system or, in other words, its ability to switch rapidly between tasks. In the second test, all the frequencies are scaled by 1.1, 1.2, ... at each iteration, until a deadline is missed. This is a uniform increase of the number of operations done by the tasks, therefore testing the ability to handle an increased but still balanced workload. The third test starts from the baseline set and increases the workload of each task by 1, 2, ... KWIPS per period at each iteration, until a deadline is missed. This increases the system's overhead while introducing unbalance. In the last test, a new task is added at each iteration, with a workload of 8 KWIPS per period and a frequency of 8 Hertz (equivalent to the third task of the baseline set). This test evaluates the performance in handling a large number of tasks.

		Benchmark No.			
		I	II	III	IV
Period duration		10000	4000	10000	10000
Policy	EDF	14 (265)	24 (42)	7 (43)	7 (73)
	LLF	14 (993)	24 (1183)	7 (491)	7 (7143)
	RR, $q/T_{\min}^{base} = 1/625$	3 (3485)	24 (3999)	3 (4867)	7 (9351)
	RR, $q/T_{\min}^{base} = 5/625$	3 (705)	24 (799)	3 (981)	7 (1870)
	RR, $q/T_{\min}^{base} = 10/625$	3 (357)	24 (399)	2 (435)	7 (935)
	PSC+BCC, $\tau_r^\circ = 500$	14 (126)	24 (60)	7 (126)	7 (252)
	PSC+BCC, $\tau_r^\circ = 1000$	14 (66)	24 (36)	7 (66)	7 (132)
	PSC+BCC, $\tau_r^\circ = 2000$	14 (48)	24 (24)	7 (42)	7 (84)

Table 2: Hartstone PH (Periodic Tasks, Harmonic Frequencies) series benchmark: number of iterations before first deadline miss, and (in parentheses) number of context switches in the last period of the last test iteration before that with the first miss. In the RR case the quantum q is selected as a fraction of the minimum task period (625 time units) in the baseline system, denoted by T_{\min}^{base} .

Table 2 shows the results of the PH tests. The scheduling algorithm designed

within our framework shows consistently good performances, and can outperform other standard algorithms in certain operational conditions for aspects such as deadline misses.

Complexity evaluation. Let σ_{POL} denote the time spent during one round in running the scheduler *POL*. In our experiments, *POL* is one of *RR*, *SRR* (Selfish Round Robin³), and *PSC + BCC*.

$$\begin{aligned}\sigma_{RR} &= N \cdot t_{\rightarrow} + N \cdot t_c, \\ \sigma_{SRR} &= N \cdot t_{\rightarrow} + N \cdot t_c + N^2 \cdot (t_S + t_{\Pi}), \\ \sigma_{PSC+BCC} &= N \cdot t_{\rightarrow} + N \cdot t_c + (N+1) \cdot t_s + \\ &\quad (2N+1) \cdot t_{\Sigma} + (2N+2) \cdot t_{\Pi}\end{aligned}\tag{7}$$

The expressions above take into account the arithmetic operations necessary to execute the controller's code. Then, if we denote the quantum (where applicable) by q , the total duration of one round is given by

$$\tau_{r,RR} = N \cdot q, \quad \tau_{r,SRR} = N_w \cdot q, \quad \tau_{r,PSC+BCC} = \tau_r^\circ\tag{8}$$

where $N_w \leq N$ is the number of tasks in the waiting queue in the *SRR* case.

Correspondingly, the overall time complexity of the algorithms can be computed. With *PSC*, it is independent of the number of tasks and can be tuned by changing the round duration parameter. In addition, it is interesting to compare the complexity of our *PSC + BCC* algorithm against the *RR* algorithm (an open-loop policy) and the *SRR* algorithm (a closed-loop variant of *RR*, where the possibility of moving tasks between queues provides the feedback mechanism). It turns out that our *PSC + BCC* algorithm is computationally slightly more complex than *RR*; however, the more complex properties that *PSC + BCC* can guarantee — such as convergence to the desired distribution in the presence of disturbances — pay off the additional cost. *SRR*, on the other hand, can enforce similar properties and has a greater computational complexity than *PSC + BCC*. The comparison with *SRR* requires, however, further investigation, because the parameters of *SRR* do not seem to have an entirely clear interpretation within the control-theoretical framework.

5 Conclusion and future work

We presented a framework, based on control theory, to approach the scheduling problem. The approach clearly separates the models of the processor and of the scheduler. This enables the re-use of a vast repertoire of control-theoretical techniques to design a scheduling algorithm that achieves certain requirements. Algorithm design is then essentially reduced to controller synthesis. We showed how to compare the resulting algorithms to existing ones, and the advantages that are peculiar to our approach.

This paper focused on developing the components responsible for the computation of budgets and the selection of tasks. Future work will focus on the design of the intervention policies. This aspect can still be approached within the same framework, by analyzing the effects of different policies on the model equations and on the overall system performance. Moreover, we plan to refine the complexity evaluation of scheduling algorithms.

³Notice that the *SRR* is a useful example as it provides an adaptation mechanism.

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