Feedback Scheduling for Energy-Efficient Real-Time Homogeneous Multiprocessor Systems

Mason Thammawichai and Eric C. Kerrigan

Abstract—Real-time scheduling algorithms proposed in the literature are often based on worst-case estimates of task parameters. The performance of an open-loop scheme can be degraded significantly if there are uncertainties in task parameters, such as the execution times of the tasks. Therefore, to cope with such a situation, a closed-loop scheme, where feedback is exploited to adjust the system parameters, can be applied. We propose an optimal control framework that takes advantage of feedback control techniques to solve a real-time multiprocessor scheduling problem with uncertainty in task execution times, with the objective of minimizing the total energy consumption. Specifically, we propose a linear programming based algorithm to solve a workload partitioning problem and adopt McNaughton’s wrap around algorithm to find the task execution order. The simulation results illustrate that our feedback scheduling algorithm can save energy by as much as 40% compared to an open-loop method for two processor models, i.e. a PowerPC 405LP and an XScale processor.

I. INTRODUCTION

Computing devices, such as server farms, data centers, portable devices and desktops, will consume more than 14% of global electricity consumption by 2020 [1]. As the performance and speed of processors increase, the challenges in designing these future high-performance computing systems are processor power consumption and heat dissipation. Moreover, these systems may need to operate under tight energy requirements while guaranteeing a quality of service.

As specified by the Advanced Configuration Power Interface (ACPI) [2], which is an open industry standard for device configuration as well as power and thermal management, the power usage of a device can be controlled by various methods. For example, by controlling the time in the idling power states, changing the operating frequency by various methods. For example, by controlling the time management, the power usage of a device can be controlled energy requirements while guaranteeing a quality of service.

Dynamic Voltage and Frequency Scaling (DVFS) techniques have been widely used as an energy management scheme in modern computing systems. Typically, a processor running at a higher clock frequency consumes more energy than a processor running at a lower clock frequency. Hence, DVFS techniques aim to reduce the power/energy consumption by dynamically controlling the CPU operating frequency/voltage to match the workload. Since timeliness is an important aspect for real-time systems, the main consideration in applying DVFS is to ensure that deadline constraints are not violated.

Though a lot of work has been proposed to solve real-time scheduling problems, most of them are based on the assumption that the computational task parameters, e.g. the task’s execution time, period and deadline, do not change. In other words, they are open-loop controllers. Though an open-loop scheduler can provide good performance in a predictable environment, the performance can be degraded in an unpredictable environment, where there are uncertainties in task parameters. Specifically, the actual execution time of the task can vary by as much as 87% of measured worst-case execution times [3]. Since it is often the case that the task parameters are based on the worst-case, it follows that the system workload is overestimated, resulting in higher energy consumption due to non-optimal solutions. Therefore, in this work, we aim to apply feedback methods from control theory to address a scheduling problem subjected to time-varying workload uncertainty.

Only a few works have adopted feedback methods from control theory to cope with a dynamic environment for real-time scheduling. For example, [4] proposed an energy-aware feedback scheduling architecture for soft real-time tasks for a uniprocessor. A proportional controller adjusts the workload utilization through a variable voltage optimization unit. Specifically, the controlled variable is the energy savings ratio and the manipulated variable is the worst-case utilization.

Similarly, [5] proposed a feedback method for estimating execution times to improve the system performance, i.e. the number of tasks that meet deadlines and the number of tasks that are admitted to the system. That is, the estimated execution time is calculated at each decision time interval based on the deadline miss and rejection ratios.

In [6], a feedback method was developed for a uniprocessor hard real-time scheduling problem with DVFS to cope with varying execution time tasksets. In the same manner, the actual execution time of the task is fed back to a PID controller to adjust the estimated execution time of the task, as well as the execution frequency.

A two-level power optimization control on a multi-core real-time systems was proposed in [7]. At the core-level, the utilization of each CPU is monitored and a DVFS scheme is implemented in response to uncertainties in task execution.

1The utilization of the task is defined as the ratio between the task execution time and its deadline. For this work, we will use the term ‘density’ rather than utilization; in the literature, utilization is often used for a special case of a periodic taskset, i.e. when the task deadline is equal to its period.
times in order to obtain a desired utilization. To further reduce power consumption, task reassignment and idle core shutdown schemes were employed at the processor level.

All of the work in this area only consider feedback of real-time scheduling as regulation problems. However, our work will consider real-time multiprocessor scheduling as a constrained optimal control problem [8], which can be combined with a feedback scheme to handle uncertainties in an unpredictable scheduling environment, as is done in model predictive control [9]. Our proposed scheme would also be known as a slack reclamation scheme in the real-time scheduling literature, in which the slack time due to early completion of a task is exploited to reduce energy consumption by decreasing the operating speed of the remaining tasks in the system [10], [11].

The main contributions of this paper are:

- A feedback and optimal control framework is proposed to solve a real-time scheduling problem with uncertainty in task execution times on a homogeneous multiprocessor system with DVFS capabilities.
- A convex optimization formulation is proposed to solve a workload partitioning problem.
- The first energy-optimal scheduling algorithm to solve multiprocessor scheduling with aperiodic tasksets.
- Though we introduce the problem with discrete frequency level systems, the framework can be applied to continuous frequency multiprocessor systems by simply replacing the workload partitioning algorithm by the nonlinear programming formulation proposed in [8].

Details of the system model is given in Section II. The feedback scheduling framework is presented in Section III. That is, Section III-A describes scheduling as an optimal control problem, Section III-B presents an LP formulation to solve the problem and the overall feedback scheduling architecture is provided in Section III-C. Simulation results to demonstrate the performance of our feedback algorithm are given in Section IV. Lastly, we summarise the results and discuss future work in Section V.

II. TASK AND PROCESSOR MODELS

A task $T_i$ is assumed to be aperiodic and defined as a triple $T_i := (b_i, c_i, d_i)$, where $b_i$ is the task arrival time, $c_i$ is the estimated number of CPU cycles to complete the task and $d_i$ is the task relative deadline, i.e. a task $T_i$ arriving at time $b_i$ has a deadline at time $b_i + d_i$. The estimated minimum execution time $\bar{x}_i$ is the estimated execution time of the task $T_i$ when executed at the maximum clock frequency $f_{\text{max}}$, i.e. $\bar{x}_i := c_i/f_{\text{max}}$. The minimum task density $\delta_i$ is defined as the ratio between the task minimum execution time and deadline, i.e. $\delta_i := \bar{x}_i/d_i$. The actual minimum execution time of the task $y_i$ is the actual execution time when the task is executed at clock frequency $f_{\text{max}}$, i.e. $y_i := \gamma_i \bar{x}_i$, where $0 < \gamma_i \leq 1$ is the estimation factor. Note that the actual execution time of the task is not known until the task has finished. We will assume that the tasks can be preempted at any time, i.e. the execution of the task on a processor can be suspended in order to start executing another task. Moreover, task migration is allowed, i.e. execution is allowed to be suspended on one processor and able to be continued on another processor. There is no delay with task preemption or migration, since we assume that the delay is added to the estimated task execution times or that the delay is negligible. Lastly, it will also be assumed that tasks do not have any resource or precedence constraints, i.e. the task is ready to start upon its arrival time.

For this work, we assume a practical processor model, i.e. a processor has a finite set of operating frequency levels. Additionally, the processors are homogeneous, that is, having the same set of operating frequencies and power consumptions. The processor voltage/frequency can be adjusted individually using a DVFS technique.

The energy consumed during the time interval $[t_1, t_2]$ is

$$E(t_1, t_2) := \int_{t_1}^{t_2} P(s(t))dt,$$

where $P(s(t))$ is the instantaneous power consumption of executing a task at an execution speed $s(t)$, defined as the ratio between the operating frequency $f(t)$ to $f_{\text{max}}$, i.e. $s(t) := f(t)/f_{\text{max}}$. The energy consumed by executing and completing task $T_i$ at a constant speed $s_i$ is the summation of the energy of the active and idle modes, hence $E(t_1, t_2) = \mathcal{M}_i(P_{\text{active}}(s_i) - P_{\text{idle}})/s_i + P_{\text{idle}}(t_2 - t_1)$, where $P_{\text{active}}(s_i)$ is the power while active and $P_{\text{idle}}$ is the idle power.

III. FEEDBACK SCHEDULING

A. Continuous-time Optimal Control Problem

This section recalls an optimal control formulation of a multiprocessor scheduling problem with the objective to minimize the total energy consumption [8]. The problem statement is: Given $m$ homogeneous processors and $n$ real-time tasks, determine a schedule for all tasks within a time interval $[t_1, t_2]$ that solves the following infinite-dimensional continuous-time optimal control problem:

minimize

$$x(\cdot), a(\cdot) \int_{t_1}^{t_2} \sum_{i, k, q} a_{ik}^q(t)(P(s^q) - P_{\text{idle}})dt$$

subject to

$$x_i(b_i) = x_i, \quad \forall i$$

$$x_i(t) = 0, \quad \forall i, \ t \notin [b_i, b_i + d_i]$$

$$\dot{x}_i(t) = -\sum_{k, q} s^q a_{ik}^q(t), \quad \forall i, \ t, \ \text{a.e.}$$

$$\sum_{k, q} a_{ik}^q(t) \leq 1, \quad \forall i, \ t$$

$$\sum_{i, q} a_{ik}^q(t) \leq 1, \quad \forall k, t$$

$$a_{ik}^q(t) \in \{0, 1\}, \quad \forall i, \ k, \ q, \ t$$

where $x_i(t)$ is the remaining estimated minimum execution time of task $T_i$, $a_{ik}^q = 1$ denotes that processor $k$ executes task $T_i$ at speed level $q \in Q := \{1, \ldots, \ell\}$ at time $t$, where $s^q$
is the corresponding speed and \( \ell \) is the total number of non-idle speed levels of a processor. If \( I := \{1, \ldots, n\}, K := \{1, \ldots, m\} \) then \( \forall i, \forall k, \forall q, \forall t \) will be used as short-hand for \( \forall i \in I, \forall k \in K, \forall q \in Q, \forall t \in [t_1, t_2] \), respectively.

The objective is to minimize energy consumption. The estimated execution time and deadline constraints are specified in (2) and (2c), respectively. The scheduling dynamic (2d) is represented by a flow model (an integrator) with the state \( x \) and control input \( a := (a_1, \ldots, a_d) \). Constraints (2e) and (2f), respectively, ensure that at all times a task is not assigned to at most one non-idle processor and vice versa. Constraint (2g) indicates assignment variables are binary.

B. Discrete-time Optimal Control Problem as an LP

It was shown in [8] that for a practical system, where each processor has a discrete set of operating frequencies, the problem (2) can be simplified into two steps: (i) solving a workload partitioning problem using a linear programming (LP) formulation and (ii) given a solution to the workload partitioning problem, solve a task ordering problem using McNaughton’s wrap around algorithm [12].

1) Workload Partitioning: By relaxing the constraint (2g) so that the value of \( a \) is interpreted as the fraction of the task execution time during each discretization time interval, the workload partitioning problem can be formulated as a finite-dimensional LP (annotated as LP-DVFS). For this purpose, let \( w_i^q[\mu] \in [0, 1] \) denote the fraction of the interval \([\tau_\mu, \tau_{\mu+1}]\) during which task \( T_i \) is to be executed at speed level \( q \).

Let \( T := \{T_i \mid i \in I\} \) denote a taskset composed of all active tasks within \([t_1, t_2]\). Let \( \{\tau_0, \tau_1, \ldots, \tau_N\} \) be the set of times corresponding to the distinct task arrival times and deadlines within the time interval \([t_1, t_2]\), where \( t_1 = \tau_0 < \tau_1 < \cdots < \tau_N = t_2 \). Let \( U := \{0, 1, \ldots, N-1\} \) and define a task arrival time mapping \( \Phi_0 : T \to U \) by \( \Phi_0(T_i) := \mu \) such that \( \tau_\mu = b_\mu \), \( \forall T_i \in T \), a task deadline mapping \( \Phi_d : T \to U \cup \{N\} \) by \( \Phi_d(T_i) := \mu \) such that \( \tau_\mu = b_\mu + d_\mu \), \( \forall T_i \in T \) and \( U_i := \{i \in U \mid \Phi_d(T_i) \le \mu < \Phi_d(T_{i+1})\}, \forall i \in I \).

The workload partitioning statement is: Given \( m \) homogeneous processors and a taskset \( T \) with \( n \) tasks, determine the fraction of task execution times within each time interval that solves the following discrete-time optimal control problem:

\[
\min_{\xi, \mu, i, q} \sum_{\mu, i, q} (\tau_{\mu+1} - \tau_\mu) w_i^q[\mu] (P(s^q) - P_{idle})
\]

subject to

\[
\xi_i(\Phi_0(T_i)) = x_i \\
\xi_i[\mu] = 0 , \quad \forall i , \mu \notin U_i \\
\xi_i[\mu+1] = \xi_i[\mu] - (\tau_{\mu+1} - \tau_\mu) \sum_q s_q w_i^q[\mu] , \quad \forall i , i \in U_i \\
\sum_q w_i^q[\mu] \le 1 , \quad \forall i, \mu \in U \\
\sum_{i,q} w_i^q[\mu] = m , \quad \forall \mu \in U \\
0 \le w_i^q[\mu] \le 1 , \quad \forall i, q, \mu \in U
\]

where the state \( \xi_i[\mu] \) is the estimated minimum execution time of task \( T_i \) and \( w_i^q[\mu] \) can be interpreted as the value of a control input at time instant \( \tau_\mu \).

The constraints on the dynamics (3b)–(3d) correspond to (2b)–(2d). Constraint (3g) assures that a task will not be assigned to more than one processor at a time. Constraint (3f) guarantees that the total workload during each time interval will not exceed the system capacity. Lastly, (3e) provides the appropriate lower and upper bounds on \( w_i^q[\mu] \).

The functions \( \xi : U \cup \{N\} \to \mathbb{R}^n \) and \( w := (w^1, \ldots, w^d) : U \to \mathbb{R}^{m \times n} \), map finite sets to the Euclidean space, hence it follows that (3) is equivalent to a finite-dimensional LP with a tractable number of decision variables and constraints. Note that many of the components of the solution are always zero and that the LP is highly structured with sparse matrices and vectors. These facts can be exploited to develop efficient tailor-made solvers, as in the literature on model predictive control [9].

Note that \( w_i^q[\mu] \) does not have a subscript \( k \) to indicate processor assignment, which is done during task ordering.

2) Task Ordering: Given a solution to (3), we can find an execution order for all tasks within each time interval such that no task is executed on more than one non-idle processor at each time instant. This can be done using McNaughton’s wrap around algorithm [12], which is detailed in Algorithm 1 for the problem considered here.

The algorithm proceeds as follows for a given interval \([\tau_\mu, \tau_{\mu+1}]\). The fractions \( \{w_i^q[\mu] \mid i \in I, q \in Q\} \) care

\[
\begin{align*}
1: & \text{ INPUT } \{w_i^q[\mu] \in [0, 1] \mid i \in I, q \in Q\} \\
2: & \sigma_i^q[\mu] \leftarrow 0, \eta_i^q[\mu] \leftarrow 0, \forall i, k, q \\
3: & k \leftarrow 1 \\
4: & \text{ for } i = 1, \ldots, n \text{ do} \\
5: & \quad \text{ for } q = 1, \ldots, \ell \text{ do} \\
6: & \quad \quad \text{ if } i = 1 \text{ then} \\
7: & \quad \quad \quad \eta_i^q[\mu] \leftarrow w_i^q[\mu] \\
8: & \quad \quad \quad \text{ else} \\
9: & \quad \quad \quad \quad \text{ if } \eta_i^q[\mu] + w_i^q[\mu] \le k \text{ then} \\
10: & \quad \quad \quad \quad \quad \sigma_i^q[\mu] \leftarrow \eta_i^q[\mu] \\
11: & \quad \quad \quad \quad \quad \eta_i^q[\mu] \leftarrow w_i^q[\mu] + \sigma_i^q[\mu] \\
12: & \quad \quad \quad \quad \text{ else} \\
13: & \quad \quad \quad \quad \quad \sigma_i^q[\mu] \leftarrow \eta_i^q[\mu] \\
14: & \quad \quad \quad \quad \quad \eta_i^q[\mu] \leftarrow 1 \\
15: & \quad \quad \quad \quad \quad \eta_i^q[\mu] \leftarrow w_i^q[\mu] - (\eta_i^q[\mu] - \sigma_i^q[\mu]) \\
16: & \quad \quad k \leftarrow k + 1 \\
17: \quad \text{ end if} \\
18: \quad \text{ end for} \\
19: \text{ end for} \\
20: \text{ end for}
\end{align*}
\]
TABLE I: Execution workload partition example

| Task | \( w_{ik}^1 \) | \( w_{ik}^2 \) | \( T_i \) |
|------|----------------|----------------|------|
| T1   | 0.1            | 0.2            | T1   |
| T2   | 0              | 0.5            | T2   |
| T3   | 0.2            | 0.4            | T3   |
| T4   | 0.4            | 0              | T4   |

(a) Tasks are aligned along the real number line.

(b) Each chunk of length 1 is assigned to a processor.

Fig. 1: Feasible schedule at time interval \([\tau_i, \tau_{i+1}]\) obtained by McNaughton’s wrap around algorithm, where the number in each box is \( w_{ik}^q \).

Given a solution to (3) and the output from Algorithm 1 for all intervals. It follows from the properties of McNaughton’s algorithm [12] that only one task is assigned to a processor at a time if \( a \) is chosen to be piecewise constant such that

\[
\sigma_{ik}^q(t) = 1 \quad \text{when} \quad \sigma_{ik}^q(\mu)(\tau_{i+1} - \tau_i) \leq t - \tau_i < \eta_{ik}^q(\mu)(\tau_{i+1} - \tau_i),
\]

and \( \sigma_{ik}^q(t) = 0 \) otherwise, \( \forall i, k, q \). After verifying that (4) holds, one can show that (2b)–(2g) are satisfied.

Given a solution to (2) and the output from Algorithm 1, for all intervals. It follows from the properties of McNaughton’s algorithm [12] that only one task is assigned to a processor at a time if \( a \) is chosen to be piecewise constant such that

\[
\sigma_{ik}^q(t) = 1 \quad \text{when} \quad \sigma_{ik}^q(\mu)(\tau_{i+1} - \tau_i) \leq t - \tau_i < \eta_{ik}^q(\mu)(\tau_{i+1} - \tau_i),
\]

and \( \sigma_{ik}^q(t) = 0 \) otherwise, \( \forall i, k, q \). After verifying that (4) holds, one can show that (2b)–(2g) are satisfied.

### C. Feedback Scheduler

As can be seen, our open-loop optimal control problem is based on the estimated minimum execution time \( \bar{x} \). The task will often finish earlier than expected, i.e. the actual minimum execution time \( y \) is often less than \( \bar{x} \). Consider Figure 2, which illustrates a fluid path of executing a task \( T_i \). Our open-loop algorithm follows a different path from the one that we really want to follow, i.e. the dotted line, due to uncertainty in task execution times. In other words, the open-loop algorithm can provide a solution that is overestimating the system workload, leading to higher energy consumption, due to the fact that the system operates at an unnecessarily higher speed. Therefore, it is better to feed back information whenever (i) a task finishes or (ii) a new task arrives at the system, in order to recalculate a new control action to respond to the changing workload.

The overall architecture of our feedback scheduling system is given in Figure 3, where the scheduler is called at two scheduling events. One occurs when a task finishes its
required executing workload/cycles on one of the processors and the other when a new task arrives. The scheduler is composed of two sub-units, i.e. a workload partitioning unit and a task ordering unit. By solving (3), the workload partitioning unit provides control input $w$ to the task ordering unit, which then uses McNaughton’s wrap around algorithm to produce a valid schedule to the execution unit.

IV. SIMULATION AND RESULTS

To evaluate the performance of our feedback scheme, we consider a set of aperiodic tasks to be scheduled on two commercial processors, namely a PowerPC 405LP and an XScale. The details of the two processors are given in Table II. Two homogeneous systems composed of two processors of the same type were chosen. The energy consumed by executing each taskset, listed in Table III, were evaluated.

The minimum taskset density $D := \sum_{i \in I} \delta_i$, a measurement of the utilization of computing resources in a given time interval, is defined as the sum of minimum task densities of all tasks within the system. The LP (3) was modelled using OPTI TOOLBOX [16] and solved with SoPlex [17].

For this simulation, we only consider the scheduling event when a task finishes. Three algorithms are compared: (i) Feedback LP-DVFS, which is our LP-DVFS + McNaughton’s wrap around algorithm proposed in Section III-C, (ii) Open-Loop LP-DVFS, which is our LP-DVFS without feedback information on finishing tasks, and (iii) No mismatch/Ideal, which is our LP-DVFS with the actual minimum task execution times equal to the estimated, i.e. $\bar{x}_i = y_i$

Figure 4 shows results from executing the tasksets in Table III onto two homogeneous multiprocessor system, composed of two of each processor type, with the estimation factor $\gamma_i = 0.5$, $\forall i \in I$. The vertical axis is the total energy consumption normalised by the Open-Loop. The feedback scheme starts to perform better than the open-loop scheme only when the density is more than 1. Moreover, the percentage saving of the XScale system is less than that of the PowerPC’s. This is due to the differences in the distribution of speed levels of the two processor types, i.e. the XScale processor has more evenly distributed speed levels than that of the PowerPC; therefore, the optimizer can select the operating speed level that is closer to the optimal continuos speed value.

The results from varying the estimation factor of the taskset with $D = 1.25$ are shown in Figure 5. Note that, for this simulation, the estimation factors of all tasks are the same. For a PowerPC system, the energy saving is high when the estimation factor is low. In addition, the difference between the energy consumed by the feedback strategy and the ideal decreases as the estimation factor increases. On the other hand, for an XScale system, the maximum energy saving does not occur when the estimation factor is the lowest, but rather occurs at $\gamma = 0.5$. Furthermore, the energy consumption difference between the feedback and optimal/ideal is larger than that of the PowerPC’s. Note that the energy saving varies with the tasksets, solutions from different LP solvers, and the task execution order. Particularly, since the solutions are not unique, the choice of selecting the task execution order has an effect on the total energy consumption.

V. CONCLUSIONS AND FUTURE WORK

A feedback method was adopted to solve a multiprocessor scheduling problem with uncertainty in task execution times. We have shown that our proposed closed-loop optimal control scheduling algorithm performs better than the open-loop algorithm in terms of energy efficiency. Simulation results suggest that the difference between closed-loop and open-loop performance can be reduced by having a more refined distribution of operating speed levels.

The work presented here can be extended in a number of ways. For a periodic task, an estimator could be incorporated to obtain a better performance. For further energy savings, a dynamic power management scheme (DPM), which determines when and how long the processor should be in the active or idle state, could also be integrated in the scheme.

Finally, note that there are many links here to model predictive control [9] and it would therefore be of interest to investigate how methods developed in that community could be applied to the scheduling problem defined here. For example, one could extend the work to the problem of optimizing over feedback policies, rather than open-loop input sequences, as was done here. Efficient numerical
methods, including distributed cooperative schemes, could also be developed to solve the LP \( \text{(3)} \) in real-time.

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