

Towards Energy-aware Optimisation of Business Processes

Beatriz López¹, Aditya Ghose², Tony Savarimuthu³, Mariusz Nowostawski⁴,
Michael Winikoff³ and Stephen Cranefield³

¹*eXiT research group, University of Girona, Girona, Spain*

²*School of Computer Science and Software Engineering, University of Wollongong, Wollongong, Australia*

³*Dept. of Information Science, University of Otago, Dunedin, New Zealand*

⁴*Faculty of Computer Science and Media Technology, Gjøvik University College, Gjøvik, Norway*

Keywords: Energy Management, Resource Allocation, Time-dependent Costs, Constraint Optimisation, Auction.

Abstract: Time dependent energy tariffs are a matter of concern to managers in organisations, who need to rethink how to allocate resources to business processes so that they take into account energy costs. However, due to the time-dependent costs, the resource optimisation problem needs to be redesigned. In this paper we formalise the energy-aware resource allocation problem, including time-dependent variable costs; and present a case study in which an auction mechanism is used to find a solution. Our results show how the choice of cost (energy, monetary, or duration) affects the schedules obtained.

1 INTRODUCTION

Increasingly, energy prices are changing from flat rates to time-dependent tariffs, which presents companies with the problem of smoothing and shifting peaks from expensive to cheaper hours. Dealing with time-dependent energy costs has been mainly studied in the context of household management (Gottwalt et al., 2011), and business process management has been mostly neglected. An exception is the proposal of Hoesch-Klohe et al. (2010) in which resources are annotated with CO_2 consumption details, which are known to the process manager that aggregates the energy costs.

This paper considers allocation and optimisation of resources in business processes while taking into account energy costs. Business processes pose particular challenges to optimisation because, unlike household energy usage, they are structured (e.g. a process may involve an extended sequence of steps), and may include structural uncertainty (e.g. the business process may include embedded decisions, so the exact tasks to be performed will not be known with certainty ahead of time).

The key contribution of the work is the problem formalisation, which includes the optimisation of resources taking into account time-dependent energy costs. With the formalisation of the problem, we aim to provide a new optimisation problem to the research

arena, the solution of which will provide new tools for business managers to support energy-aware decision-making.

We also provide an auction-based resource-allocation mechanism to illustrate with a case study the possible outcomes of the energy-aware optimisation process. However, the focus of the paper is not the technological part (auction-based resource allocation), but to provide a first approach to formalising the problem of energy-aware optimisation of business processes.

This paper is organised as follows. First we start by reviewing related work in Section 2. Next, in Section 3 we provide the formalisation of the energy-aware resource optimisation problem. In Section 4 a case study is provided, and we end in Section 5 with some discussion and ideas for further research.

2 RELATED WORK

Research on green business process management is described by Nowak et al. (2011), who identify the required changes for business processes to be environmentally aware. Focusing on energy, Ardagna et al. (2008) propose a framework that includes a control layer in which the energy consumption is optimized according to execution times. In subsequent

work, Cappiello et al. (2010) describe a tool for validating the desired energy consumption. All of these approaches are based on web services and a task is assigned to at most one service. By contrast, our work allocates a given task to bundles of services (i.e. resources).

The timeline-based scheduling work of Chien et al. (2010) is similar to our work in that they have a collection of business process instances, each of which has resource requirements. A key difference between their work and ours lies in the fact that they are able to drop business process instances. Furthermore, we deal with time-dependent costs of resources, which they do not.

Time-variable cost functions have been recently considered by the constraint community (Simonis and Hadzic, 2010), but the solution proposed can only be applied in centralised environments and is not applicable to our business process model. More generally, traditional research on the job shop problem and workflow resourcing considers a one-to-one mapping of tasks to machines, whereas we allow a task to require multiple resources. Other differences include our allowance for uncertainty in the workflow (through the presence of XOR nodes), and our use of abstract tasks.

3 PROBLEM FORMULATION

We address energy optimisation issues in the context of resource allocation for business processes. The main inputs of our problem are the tasks to be performed and their sequencing dependencies, the resources available, constraints on the time and resource availability, and the cost function that characterizes the optimisation target.

3.1 Tasks

Formally we define a set of all the task instances involved in a given workload $T = \{t_1 \dots t_m\}$. Each task has an associated duration that is not fixed, but depends on the resources used. We then define a business process instance B as being a graph $B = (V, E)$ where the vertices are one of the following: a task t_i , one of a set of XOR nodes $X = \{x_1, \dots, x_k\}$, or either the distinguished start node s or end node e . Formally $V = T \cup X \cup \{s, e\}$. As usual, E is a set of pairs of vertices (v, v') where $v, v' \in V$. Each XOR node x_i has an associated set of options: $option(x_i) = \{B_{x_i}^1, \dots, B_{x_i}^{k_i}\}$ where each of the elements of the set $B_{x_i}^j$ is a graph, as defined above. In other words, we have a top-level

graph B which may have some nodes that are themselves place-holders for one of a set of sub-graphs. We require that the tree of graphs is finite—the leaf graphs are those with no XOR nodes ($X = \{\}$).

The interpretation of XOR nodes is that eventually at run time each x_i is replaced by one of its sub-graphs $B' \in option(x_i)$. This replacement is repeated until there are no XOR nodes remaining. Since there is a choice of $B' \in option(x_i)$ for each x_i , this process is non-deterministic. It results in a “decided” graph which has $X = \{\}$, i.e. no XOR nodes.

This run-time recursive replacement of each XOR node with one of its alternative subgraphs models the “don’t know” non-determinism of workflow execution, where there may be different sub-workflows for performing a complex job, but the one that will be used for any workflow instance will be decided at run time (due to resource availability or other situational factors that we do not attempt to model).

We use $v \rightsquigarrow v'$ to denote that there is a path from v to v' , defined in the usual way¹, and use $v_1 \rightsquigarrow v_2 \rightsquigarrow v_3$ as shorthand for $v_1 \rightsquigarrow v_2 \wedge v_2 \rightsquigarrow v_3$.

We require the graph (V, E) to be well-formed, which we define to mean that there are no arcs to the start node ($\neg \exists v. (v, s) \in E$); there are no arcs from the end node ($\neg \exists v. (e, v) \in E$); there are no cycles ($\neg \exists v \in V. v \rightsquigarrow v$); and for any node $v \in V$ (apart from the start and end nodes), there is a path from s to v and from v to e ($\forall v \in (V \setminus \{s, e\}). s \rightsquigarrow v \rightsquigarrow e$).

3.2 Resources

Each task requires *resources* in order to be carried out. We define a set of known resource types $RT = \{r_1, \dots, r_n\}$. We use multisets to represent the set of available resources, *AvailRS*, and the resources that are allocated to each task in a process schedule. A multiset over RT (a “resource multiset”) is defined by a characteristic function $R : RT \rightarrow \mathbb{N}$ indicating how many copies of each element of RT appear in the multiset². For convenience we will write multisets using standard set notation³, but with the possibility of ele-

¹ $v \rightsquigarrow v' \equiv (v, v') \in E \vee (\exists v''. (v, v'') \in E \wedge v'' \rightsquigarrow v')$

²This definition of multisets does not allow for real-valued quantities of resources to be represented, but this is not a limitation: we could easily extend the notation to use real numbers, or assume that the unit of measurement is sufficiently fine grained that natural numbers are not a limitation, for instance, measuring coal in units of grams.

³We use standard definitions of multiset relations and functions (Syropoulos, 2001): $R_1 \subseteq R_2 = \forall r \in RT. R_1(r) \leq R_2(r)$. We distinguish between a maximum-based set union (\cup) and an accumulating union (\oplus): $R_1 \cup R_2 = g$ where $\forall r \in RT. g(r) = \max(R_1(r), R_2(r))$ and $R_1 \oplus R_2 = g$ where $\forall r \in RT. g(r) = R_1(r) + R_2(r)$.

ments appearing multiple times. We will also use the abbreviation a^n to represent n copies of an element, e.g. $\{a^2, b\} = \{a, a, b\}$.

Each resource type has associated monetary and energy costs. As discussed earlier, a key requirement is that these costs may vary over time. Formally we define the monetary cost $cost(\tau_1, \tau_2, r_i)$ and energy cost $energy(\tau_1, \tau_2, r_i)$ as being functions from a time interval $[\tau_1, \tau_2]$ (i.e. $\tau_1 \leq t \leq \tau_2$, where $\tau_1 < \tau_2$, $\tau_1, \tau_2 \in \mathbb{N}$) and a resource type $r_i \in RT$ to a cost (a real number), representing the *total* cost of *one* unit of resource type r_i over the given time interval.

We also define time-dependent monetary and energy *set-up* costs, $setup.cost(r, t_1, \tau_1, t_2, \tau_2)$ and $setup.energy(r, t_1, \tau_1, t_2, \tau_2)$, representing additional costs (or cost savings) that apply when a resource of type r is used for a task t_1 starting at time τ_1 and the next task for the resource is t_2 starting at τ_2 (not necessarily immediately after the end of t_1). A resource type r may also have a minimum set-up time that must be allowed between its use for a task t_1 starting at τ_1 and its next task t_2 , denoted $setup.time(r, t_1, \tau_1, t_2)$. Unlike the set-up cost and set-up energy cost, we assume that this does not depend on t_2 's starting time.

Note that, because our representation doesn't distinguish between different instances of a given resource type, set-up costs and times can only be non-zero for resource types where there is a single instance available, i.e. $AvailRS(r) = 1$. We use RT^1 to denote those resource types for which exactly one instance is available.

Finally, we generalise the set-up costs and times to also apply to XOR nodes: $setup.cost(r, t_i, start_i, x_j, start_j)$ is defined as the *maximal* cost over those tasks in the subgraphs of the XOR node that are *initial* for r . Given a set of subgraphs, a task is initial for r if it is possible for it to be the first task using r to be executed in one of the subgraphs, i.e. if we only consider tasks that use r , it is an initial task. We define $setup.cost(r, x_j, start_j, t_i, start_i)$ in an analogous way (in terms of tasks in x_j that are *final* for r), and extend this to define the set-up cost between two XOR nodes in terms of a maximum over the tasks that are final for r in the set of options for the first XOR node and those that are initial for r in the set of options for the second XOR node.

We link tasks and resources by defining $need(t_i)$ which denotes the resources that task t_i requires. In order to model "don't care" nondeterminism, where there are multiple ways of achieving a task, and we are happy to have the choice be dictated by the needs of other processes, we define $need(t_i)$ as a *set of alternative requirements*. Furthermore, for each alter-

native resource requirement, we also specify the duration of the task when those resources are allocated to it. Formally, $need(t_i) = \{(R_1, d_1^1) \dots (R_{k_i}, d_{k_i}^1)\}$, where each R_i is a multiset and each d_j^i is a natural number denoting the duration of task t_i if the j^{th} resource multiset is used.

3.3 Schedules

A *schedule* S for a business process assigns to each task a starting and ending time (respecting the sequencing constraints) and resources (such that the available resources are not exceeded at any point in time). Formally, a *schedule* S is a set of task records:

$$S = \{s_1, \dots, s_m\} \cup \{s'_1, \dots, s'_k\} \cup \{(start_s, end_s, \{\}, s), (start_e, end_e, \{\}, e)\} \quad (1)$$

There are two types of task records: s_i which correspond to tasks, and s'_j which correspond to XOR nodes. A task record s_i is a tuple $s_i = (start_i, end_i, RS_i, t_i)$ where $start_i$ is the start time of the task's performance, end_i is the completion time, RS_i is a multiset of resources assigned to the task, and t_i is the task. For convenience we include task records for the start and end nodes. These are treated as tasks that take no time to perform (so $start_s = end_s$ and $start_e = end_e$) and have no resource requirements (so $RS_s = RS_e = \{\}$). An XOR node record is a tuple $s'_j = (start_j, end_j, S_j, x_j)$ where $start_j$ and end_j are respectively the start and end times, x_j is the XOR node identifier, and S_j is a *set of sub-schedules*, i.e. a schedule for each sub-graph in $option(x_j)$. We require that $start_j$ must be the smallest of the starting times of a schedule in S_j , and similarly end_j must be the largest finishing time of a schedule in S_j .

Schedules are subject to various constraints related to tasks, set-up times, and resources. First, the task records in a schedule must satisfy a number of constraints: (i) each task t_i has a single corresponding task record s_i ; (ii) each XOR node x_j has a single corresponding XOR node record s'_j ; (iii) each task t_i is allocated the resources specified by one of the resource multisets in $need(t_i)$, and takes the corresponding specified length of time to be executed⁴; and (iv) the task start and end times must satisfy the constraint that $(t_i, t_j) \in E \Rightarrow end_i \leq start_j$.

Second, the above constraints on the schedule need to be extended to respect set-up times: where a (singleton) resource of type r is used by t_i and then by t_j , the schedule must satisfy the stronger constraint $end_i + setup.time(r, t_i, start_i, t_j) \leq start_j$. Note

⁴Formally, for some $(R_j, d_j^i) \in need(t_i)$: $R_i = R_j$, and $end_i - start_i = d_j^i$.

that t_i and t_j may not be constrained to occur in sequence. We therefore define this additional feasibility constraint using a singleton resource schedule S^r which, given schedule S and singleton resource type r , is a list of the task records for those tasks (both s_i and s'_j) that use resource r , sorted by starting time. The additional feasibility condition is then: $\forall r \in RT^1 \forall (t_i, t_j) \in S^r . end_i + setup.time(r, t_i, start_i, t_j) \leq start_j$ where $(t_i, t_j) \in S^r$ denotes the selection of adjacent elements in the list, i.e. $S^r = \langle \dots, t_i, t_j, \dots \rangle$.

Third, having defined the constraints that ensure a schedule is feasible with respect to time (including set-up times), we now define the feasibility of a schedule with respect to the available resources (*AvailRS*). We begin by defining functions that accumulate the resources used by a schedule S at time τ :

$$\begin{aligned} res(\tau, (start_i, end_i, RS_i, t_i)) &= \begin{cases} RS_i & \text{if } start_i \leq \tau \leq end_i \\ \{\} & \text{otherwise} \end{cases} \\ res(\tau, (start_j, end_j, S_j, x_j)) &= \bigcup_{s \in S_j} res(\tau, s) \\ Res(\tau, S) &= \bigoplus_{s \in S} res(\tau, s) \end{aligned}$$

The first function (*res*) takes a time τ and a task record s_i or s'_j and returns the resources required for the task at time τ , which will, for s_i , be either RS_i if the task is being performed at time τ , or the empty set; and for x_j is simply the maximum of the resources required at time τ over the sub-schedules in S_j (we need to use the maximum since we do not know which option will be selected). The second function (*Res*) takes a time τ and an entire schedule, and collects the resource requirements for a given time τ across all the tasks. Finally, a schedule S is feasible with respect to the available resources *AvailRS* if and only if $\forall \tau start_s \leq \tau \leq end_e . Res(\tau, S) \subseteq AvailRS$.

3.4 Optimisation Costs

Finally, we need to define the *cost* of a given (feasible) schedule. In fact there are three costs that we consider: the energy cost, the monetary cost, and the time. The energy cost of a schedule is defined as follows⁵:

$$\begin{aligned} Cost_e(S) &= \sum_{s \in S} Cost_e(s) \\ &+ \sum_{r \in RT^1} \sum_{(t_i, t_j) \in S^r} setup.energy(r, t_i, start_i, t_j, start_j) \\ Cost_e(s_i) &= \sum_{r \in RT} RS_i(r) \times energy(start_i, end_i, r_j) \end{aligned}$$

⁵For convenience we overload $Cost_e$ to operate on both schedule and task records.

$$Cost_e((start_j, end_j, S_j, x_j)) = \max_{S \in S_j} Cost_e(S)$$

Finally, the time cost is simply the makespan:

$$Cost_t(S) = end_e - start_s$$

In other words, the cost of a schedule is the sum of the costs for each of the task entries s_i and the XOR entries s'_j (first term) and the sum of the set-up costs (second term). Note that because the set-up cost is defined over both task and XOR nodes, and S^r includes both types of nodes, the second term includes the set-up costs between tasks and XOR nodes. To compute the cost of an individual task record, we compute for each resource type the cost of a single unit of that resource type across the given time interval, and multiply by the number of resource type units $RS_i(r)$ allocated. For XOR records, we take the maximum across the options. Similarly, we define the monetary cost, and finally, the time cost is simply the makespan: $Cost_t(S) = end_e - start_s$.

3.5 Problem Statement

Given a workload represented by graph B , the problem we are tackling is to find a feasible schedule S which minimises the three cost functions ($Cost_e$, $Cost_m$ and $Cost_t$). This is a multi-criteria optimisation problem in which we cannot assign *a priori* a greater importance to any given criterion, and so we are looking not for a single “optimal” solution, but for a set of Pareto points.

4 CASE STUDY

In this section we address the problem by means of an auction mechanism, with the aim of illustrating the different solution outcomes that arise when each of the energy, monetary cost, and makespan (i.e. time cost) are given precedence.

4.1 Auction Implementation

Auctions have been widely used for task and resource allocation among different entities with the particularity that the price of the resource allocation is decided when clearing the market (Chevalerey et al., 2006). When auctioneers demand tasks to be performed by bidders (resource agents), the mechanism is known as a reverse auction. The protocol followed in such auctions includes the main following steps:

1. The auctioneer sends a request for proposal, in which the tasks to be performed are specified.

2. The bidders answer with some offers.
3. The auctioneer decides the set of winner bids.
4. The auctioneer acknowledges the winner bidders.
5. The bidders commit the time to perform the tasks.
6. After the tasks have been performed, bidders send the auctioneer a “done” message that enacts the last step.
7. The auctioneer pays for the activity performed by the resources.

To apply an auction mechanism to our problem there are several choices to be made when designing the auction.

First, there is the choice of when the allocation of resources to tasks is performed. Resources can be scheduled in advance or following a dynamic approach, interleaving scheduling and execution of tasks. The latter approach improves the specifications of the tasks to be performed, since the uncertainty about which branch of the XOR node will be followed is cleared before resources are allocated. Due to the fact that we operate on business process instances and during the execution of the business process we may not have a sufficient amount of time to perform the scheduling, we are interested in solutions where we conduct scheduling ahead of time and booking of resources is done in advance. This approach requires us to consider overlapping resource allocation across tasks that belong to separate exclusive-or paths of the business process graph.

Second, we can perform a single auction with all of the tasks involved in a business process, or we can proceed with a sequential process, auctioning a task at a time. The latter case is useful if we can obtain a more precise picture of the requirements and constraints of a task once the preceding tasks have been allocated, as in the work of Collins and Gini (2009). However, the presence of XOR and parallel (AND) branches introduces uncertainty on which tasks should be allocated first. Thus we follow the first approach: scheduling all of the tasks in a single auction.

Third, given the set of tasks to be performed, bidders can provide bids on bundles of tasks so that the resulting mechanism is a combinatorial auction. Moreover, bidding on bundles enables the resource to express that the assignment of two (or more) consecutive tasks can improve cost, for example, to reduce the transport cost of moving some resource to a given place where the tasks should be performed (set-up costs).

Fourth, there is a single winner determination problem (WDP) to be solved. The solution of the WDP includes the allocation of both start time and

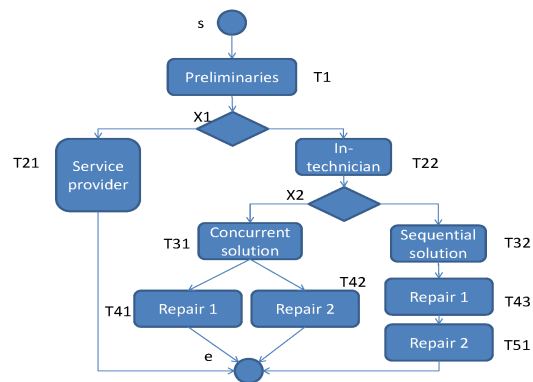


Figure 1: Business process example.

resources, for each of the tasks of a business process, taking into account the constraints specified in the problem formulation. Moreover, and thanks to the explicit definition of resource bundle alternatives associated to each task ($need(t_i)$), the winner determination algorithm decides upon a single bundle for a task based on the bids provided. From this point of view, the auction model is a combinatorial auction, since the auctioneer needs to get all of the resources of an alternative ($R_j \in need(t_i)$), or none of them. Therefore our auction model is two-fold combinatorial: bidders bid for bundles of tasks and auctioneers assign tasks to bundles of resources. This auction model is related to combinatorial exchanges (Parkes et al., 2001).

Steps four to six of the protocol involve resource acceptance and deployment after the allocation has been cleared. We are dealing with a single auction where no other request, outside this auction, is being managed by any resource agents. Thus we do not expect any rejection on behalf of agents. Failures during the tasks' execution are out of the scope of this paper (see the work of Ramchurn et al. (2009) for preventive issues).

We assume that the final step—the payment mechanism—is incentive compatible, so all of the resource agents provide truthful bids (i.e. they do not cheat when bidding).

4.2 Results

In this section we provide an auction-based solution for scheduling resources to the instances of the business process given in Figure 1. There are two XOR nodes X1 and X2. X1 decides whether the branch containing T21 or the branch containing T22 will be executed. X2 decides whether the branch containing T31 or the branch containing T32 will be executed. Note that tasks T41 and T42 can be executed concurrently (i.e. there is an AND split and join).

For each task, the bundles of resources (or single

Table 1: Resources required by each task.

Task	(Resources, Duration)
T1	({R1}, 1)
T21	({R2,R1}, 5), ({R2,R3}, 5)
T22	({R1},1), ({R4},1)
T31	({R1},1), ({R4},1)
T32	({R1},1), ({R4},1)
T41	({R3},2), ({R4},2)
T42	({R3},3), ({R4},3)
T43	({R1},2), ({R4},2)
T51	({R3},1), ({R4},1)

Table 2: Resource costs. Energy is expressed in kWh; money in euros; duration in hours.

Id	kWh	€	Duration
R1	1	160	(T1,1), (T21,4), (T22,3), (T31,2) (T32,1), (T43,1)
R2	10	200	(T21,4)
R3	5	90	(T21,4), (T41,3), (T42,4), (T51,1)
R4	3	50	(T22,1), (T31,1), (T32,2), (T41,3), (T42,3), (T43,4), (T51,2)

resources) that are capable of performing the task and the expected duration to complete the task (from the auctioneer's perspective) are given in Table 1. For example, task T21 can be performed by two different bundles of resources, {R2, R1} or {R2, R3}. The resource costs (energy costs and monetary costs) are provided in Table 2. Note that the expected duration of tasks from an auctioneer's perspective may or may not correspond to the actual ability of the resource agents (i.e. the resource agents may provide a different duration as a part of their bids and this information is internal to a resource agent). For example, the common information indicates that T21 takes 5 hours regardless of which resource bundle is taken, but the resources themselves indicate that the task actually only takes 4 hours.

We assume that day-ahead hourly prices (i.e. energy costs in kW per hour) are available (see Figure 2). This is similar to the work of Gottwalt et al. (2011). Additionally, we also assume that the resource allocation process starts at 8am.

All the tasks from all of the business process instances are allocated in a single auction. For the business process given in Figure 1, there are 9 tasks for

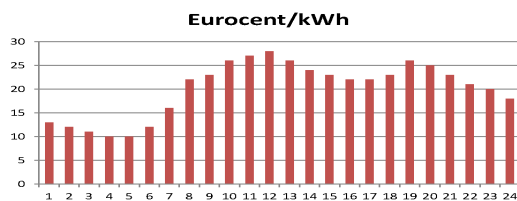


Figure 2: Day-ahead hourly tariffs.

which resources need to be allocated. They are T1, T21, T22, T31, T32, T41, T42, T43, T51. For each task, a time window is generated according to the duration estimated by the auctioneer (see Table 1) with a slack time of 2 hours. For example, since the schedule begins at 8am and T1 takes 1 hour, the request (T1, [8,11]) is sent to R1.

It should be noted that each agent may receive several requests. Agents process the requests and generate a single bid, which includes the set-up times. We have considered set-up costs in R4 (between T32 and T43, and between T43 and T51) and R3 (between T43 and T51). In all of the cases, the set-up cost consists of an extra monetary, energy and time unit cost.

Once the auctioneer collects all of the bids, the winner is determined. For determining the winner of the auction we consider three different scenarios. These three scenarios consider three attributes: the energy cost, the monetary cost and the makespan. However, the relative importance of these attributes differs in each of the scenarios.

Energy wins: the bid with the cheapest energy cost is selected. In case of a tie between energy costs, the one with the cheapest monetary cost will be preferred. Again if there is a tie, the makespan will be considered.

Money wins: the bid with the cheapest monetary cost is selected. In case of ties (the same monetary costs), energy costs will be considered for comparison. If there is a tie in energy costs, makespan will be considered.

Makespan wins: the bid with the shortest makespan is selected. In case of a tie, the cheapest energy cost is considered. If there is a tie between energy costs, the cheapest monetary cost is considered. We consider the makespan with the starting time that is closest to the earliest starting time of the activities scheduled for a given day (i.e. 8am in our case).

We note that six different scenarios can be considered for a combination of three attributes. In this paper we compare three scenarios, and we believe these scenarios are sufficient to show the consequences of using energy costs in resource allocation in business processes.

The resultant resource allocations at the end of the auction process for each of the scenarios are shown in Figure 3. Note that a resource agent can have overlapping bookings, because of the XOR nodes. The overbooking of an agent is represented as different horizontal bars in Figure 3. For example, R1 has three bookings (R1.1, R1.2 and R1.3). Note that the booking R1.1 overlaps with the other two. However, these bookings are for the tasks in XOR nodes, so these would not result in a conflicting situation at run-time,

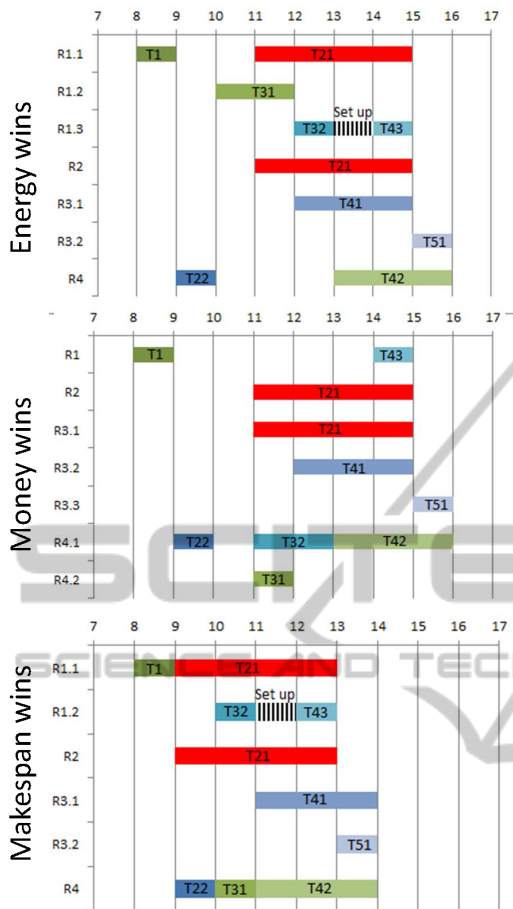


Figure 3: Resource assignment. Top: Energy wins scenario. Centre: Money wins scenario. Bottom: Makespan wins scenario.

since only one of the options of the XOR node would actually be required to be executed, i.e. if task T21 is performed, then the other tasks that R1 is allocated to (T31, T32, and T43) will not be performed.

If we look at T21, we see how the bundles are allocated differently in each of the scenarios. In the energy priority scenario (top of Figure 3) T21 is assigned to R1 and R2 (at time 11), in the monetary priority scenario T21 is assigned to R2 and R3 (also at time 11), and in the makespan scenario T21 is assigned to R1 and R3 again, but at time 9. In the figure, it is possible to observe how parallel branches (tasks T41 and T42) do not need to be executed at the same time. Finally, note that set-up costs have only been considered in the energy and makespan scenarios, when sequencing tasks T32 and T43 in R1.

To quantify the results obtained, we have measured the worst (max) and best (min) cost on each scenario. We have a range of possible costs for each scenario because of the uncertainty associated with XOR

Table 3: Comparison of three scenarios ($Cost_e$ and $Cost_€$ are in Euros, whereas $Cost_t$ is in hours).

	Scenario 1 Energy	Scenario 2 Money	Scenario 3 Makespan
Max $Cost_e$	11.58	15.38	12.28
Min $Cost_e$	2.84	3.97	3.02
Max $Cost_€$	1760.00	1320.00	1760.00
Min $Cost_€$	780.00	560.00	780.00
Max $Cost_t$	8.00	8.00	6.00
Min $Cost_t$	7.00	8.00	5.00

nodes: we don't know in advance which branch will be taken. The results obtained are shown in Table 3. If we compare the worst case energy costs between scenarios 1 and 2, the energy cost in scenario 2 is 33% more than scenario 1 (11.58 vs. 15.38). The monetary cost in scenario 1 is 33.3% more than in scenario 2 (1760 vs. 1320). In the best case monetary cost scenario, the difference in monetary cost between scenarios 1 and 2 increases to 39% (780 vs. 560). However, in this case scenario 1 has a lower makespan than scenario 2. Money and energy are moving in different scales (hundreds versus tens). However, with our experiments we are showing how the resource selection changes the energy costs. In other scenarios, energy could be more expensive.

In the makespan scenario (scenario 3), the monetary cost is the same as in scenario 1, however, the energy cost increases by 6% both in the best and worst case scenarios when compared to scenario 1. It should be noted that resources are more idle in scenario 1 than scenario 2 (worst case make span of 8 vs. 6).

The results presented in Table 3 show three what-if scenarios modelled, which can be valuable for decision makers (e.g. managers of the business processes). They can use this information to consider trade-offs between alternatives. For example, a manager currently employing the makespan strategy (scenario 3), can now consider the trade-off in moving towards a scenario where energy costs are minimised (i.e. scenario 1).

5 DISCUSSION AND FUTURE WORK

This paper presents an approach that considers energy as one of the attributes for optimising resource allocations in business processes. Towards that end, this paper presents the problem formalisation and discusses an auction mechanism that can be employed. One of the key contributions of this paper is the consideration of time-dependent energy costs as a part of scheduling and resource allocation, which has not been pre-

viously considered by work on BPM.

We used an auction mechanism to illustrate a possible instantiation of the problem formalisation and different outcomes, depending on the cost focus: energy, price and makespan. They have been analyzed using three what-if scenarios, to show how business managers can consider the consequences of considering energy during the resource allocation process.

Considering energy as a key component in scheduling and resourcing business process executions offers interesting challenges. For example, for an organisation to adhere to the ISO norms of being energy efficient and also consuming green energy (ISO, 2011), an organisation may choose to negotiate a deal with the energy provider based on the energy signature (or energy consumption shape curve) for a particular day. Energy providers can offer special rates for those companies that adhere to their expected energy shape (i.e. energy usage at different hours of the day).

This leads to other interesting scenarios such as companies offering auctions on excess surplus energy to those that need some additional energy, similar to the dynamic coalition formation scenario considered for the construction of virtual power plants (Mihailescu et al., 2011). One approach to address this problem is to enable Workflow Management Systems (Ehrler et al., 2005) in charge of business process resource allocations to coordinate their activities with Energy Management Systems (EnMS) that are in charge of company energy policy (Roche et al., 2010). An EnMS can facilitate choosing external resources that closely align with the energy objective functions of a given organisation.

REFERENCES

- Ardagna, D., Cappiello, C., Lovera, M., Pernici, B., and Tanelli, M. (2008). Active energy-aware management of business-process based applications. In *Service-Wave '08*, pages 183–195. Springer-Verlag.
- Cappiello, C., Fugini, M., Gangadharan, G., Ferreira, A., Pernici, B., and Plebani, P. (2010). First-step toward energy-aware adaptive business processes. In *On the Move to Meaningful Internet Systems: OTM 2010*, volume 6428 of *LNCS*, pages 6–7. Springer.
- Chevalyere, Y., Dunne, P. E., Endriss, U., Lang, J., Lemaître, M., Maudet, N., Padget, J., Phelps, S., Rodríguez-Aguilar, J. A., and Sousa, P. (2006). Issues in multiagent resource allocation. *Informatica*, 30:2006.
- Chien, S. A., Tran, D., Rabideau, G., Schaffer, S. R., Mandl, D., and Frye, S. (2010). Timeline-based space operations scheduling with external constraints. In *International Conference on Automated Planning and Scheduling (ICAPS)*, pages 34–41. AAAI.
- Collins, J. and Gini, M. (2009). Scheduling tasks using combinatorial auctions: the MAGNET approach. In Adomavicius, G. and Gupta, A., editors, *Business Computing*, volume 3 of *Handbooks in Information Systems*, pages 263–294. Emerald.
- Ehrler, L., Fleurke, M., Purvis, M., Tony, B., and Savarimuthu, R. (2005). Agent based workflow management systems (WfMS): JBees - A distributed and adaptive WfMS with monitoring and controlling capabilities. *Journal of Information Systems and e-Business Management*, 4(1):5–23.
- Gottwalt, S., Ketter, W., Block, C., Collins, J., and Weinhardt, C. (2011). Demand side management – A simulation of household behavior under variable prices. *Energy Policy*, 39(12):8163–8174.
- Hoesch-Klohe, K., Ghose, A., and Lê, L.-S. (2010). Towards green business process management. In *Proceedings of the IEEE International Conference on Services Computing (SCC)*, pages 386–393.
- ISO (2011). Energy management systems – requirements with guidance for use. ISO 50001:2011, <http://www.iso.org/iso/> (Accessed: 21.2.2012).
- Mihailescu, R.-C., Vasiran, M., and Ossowski, S. (2011). Dynamic coalition formation and adaptation for virtual power stations in smart grids. In *Int. Workshop on Agent Technologies for Energy Systems (ATES)*.
- Nowak, A., Leymann, F., and Schumm, D. (2011). The differences and commonalities between green and conventional business process management. In *2011 IEEE Ninth Int. Conf. on Dependable, Autonomic and Secure Computing (DASC)*, pages 569–576.
- Parkes, D. C., Kalagnanam, J., and Eso, M. (2001). Achieving budget-balance with Vickrey-based payment schemes in exchanges. In *Int. Joint Conf. on Artificial Intelligence (IJCAI)*, pages 1161–1168.
- Ramchurn, S. D., Mezzetti, C., Giovannucci, A., Rodríguez, J. A., Dash, R. K., and Jennings, N. R. (2009). Trust-based mechanisms for robust and efficient task allocation in the presence of execution uncertainty. *Journal of Artificial Intelligence Research*, 35:119–159.
- Roche, R., Blunier, B., Miraoui, A., Hilaire, V., and Koukam, A. (2010). Multi-agent systems for grid energy management: A short review. In *IECON 2010 - 36th Annual Conference on IEEE Industrial Electronics Society*, pages 3341–3346.
- Simonis, H. and Hadzic, T. (2010). An energy cost aware cumulative. In *Third Int. Workshop on Bin Packing and Placement Constraints (BPPC)*, 6 pages.
- Syropoulos, A. (2001). Mathematics of multisets. In Calude, C., Paun, G., Rozenberg, G., and Salomaa, A., editors, *Multiset Processing: Mathematical, Computer Science, and Molecular Computing Points of View*, volume 2235 of *LNCS*, pages 347–358. Springer.