# Scheduling energy consumption with local renewable micro-generation and dynamic electricity prices

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***Abstract*—The electricity market is going through a deep modification as it is moving toward the integration of smart grids. Future homes will include smarter electric devices that will be easily managed from the power consumption stand point. The capability of performing short-term negotiation of energy purchases, if introduced and if efficiently exploited, will give the user the ability to reduce energy costs.**

**In this paper we discuss a scheduling problem for household tasks that will help users save money spent on their energy consumption. Our system model relies on electricity price signals, availability of locally-generated power and flexible tasks with deadlines. A case study shows that cost savings are possible but fast and efficient solutions to the scheduling problem are needed for their real world use.**

***Index Terms*—scheduling; smart grid; smart home;**

## I. Introduction

The electricity market is witnessing a transformation from monopolistic to a deregulated and competitive structure. Demand-supply mechanisms drive the electricity pricing in the wholesale electricity market, where the actors are generation companies, transmission operators and trading companies. Ordinary users of electricity at home do not have a say in this market. According to the current practice in some European countries (e.g., Germany and Italy), the users at home are offered with options to select their preferred electricity supplier company. However the contracts between a supplier and consumers span long terms (i.e. months, years). This incurs inefficiency in two ways. First, when agreed on a flat rate price, as the cost of producing electricity fluctuates, the production company gets varying profit margins. This reflects to the end consumer as higher bills if the company makes a over prediction and as loss for the company in the case of under prediction. Secondly, consumers may be bound to a costly contract even a cheaper supplier emerges at some point in time. Both the suppliers and consumers would benefit if it was possible to make short-term contracts that are based more on the spot price of electricity. Despite the economic convenience, studies show that customers are not very willing to take the burden to continuously change their tariffs manually [1], [2].

The aforementioned pricing mechanism brings inefficiency in pricing of electricity for consumers at home [3] and calls for the creation of a healthy retail electricity market that is based on the demand and supply of electricity. This transformation should allow for an optimization of electricity usage: from one side the users should be able to negotiate short-term (e.g., hourly based) contracts with providers with the goal of obtaining lowest energy prices; from the other side, energy providers will be able to change their prices depending on market conditions, thus optimizing, by induction, the energy usage of the users. The relation between electricity demand and electricity prices at each given interval of time will be exploited: the higher the demand, the higher the prices.

Now that the electricity grid is evolving to accommodate distributed generation from various sources of energy (e.g., wind, solar, CHP) at different scales (e.g., individual owners, virtual power plants), a transformation of the electricity market is required to embrace direct user involvement in determining the retail market price of electricity. Individuals, or consortia of individuals, will be able to run their own green electricity generator, thus leveraging on local energy micro-generation.

This new electricity market will change the way in which electric devices are used: some devices will not be started immediately on user request; the user, instead, will be able to set an earliest starting time (that may be the current time) and a deadline for the operations of these devices; the system, then, will schedule the programmed task with the goal of both satisfying the deadline and of optimizing energy costs. Some other devices, of course, will still need to be started as soon as the user requests it. For example, the user will be able to program his washing machine and to specify that the washing task should be performed at most in 10 hours. The system will then schedule the washing task to minimize energy costs and to finish in at most 10 hours. On the opposite, the user will be able to start an hair drier just by pushing a button as usual.

The short-time negotiation of electricity should be, to some extent, transparent to the users: they (either directly or with the help of experts) should set the negotiation policies and the system should be able to autonomously perform all the required operations. To enable automatic negotiation each house should be equipped with a controller. The controller should be interfaced with the electric devices at home and it should be able to capture their requests. The controller should also be able to communicate with energy providers both to obtain price updates and to negotiate short-time agreements.

This mechanism can be extended to work at building or neighborhood level by using distributed controllers.

The aforementioned controller should be able to compute the best scheduling for the programmed tasks with the goal of minimizing costs while meeting all the deadlines. In this paper we discuss this scheduling problem and we show how using the task scheduler can improve usage of energy and lower costs for the users. This approach only targets savings on what we call as flexible household tasks. These tasks amount to at most 11% of total energy consumption by end user in EU residential buildings [4].

Eßer et al discuss in [5] the scheduling problem for home appliances. They schedule home appliances a day-ahead assuming the correct knowledge of the price signal. In our work the scheduling is performed on finer grained periods of time and is done at shorter terms. Furthermore, our scheduling problem also takes into account local micro-generation of energy.

In [6], authors address the problem of scheduling hard real-time tasks in wireless sensor nodes that harvest energy and propose an optimal algorithm called lazy scheduling algorithm. The problem of scheduling tasks in a harvested power-aware way is similar to the one of scheduling tasks in presence of locally-generated power; however, in that case the problem is related to single-machine scheduling and it is not applicable to our system model.

More in general, the one of scheduling tasks on limited resources is a well known problem in many areas of computer science and of other fields. An area in which scheduling is especially important is the one of operating systems. Scheduling problems in real time operating systems are especially similar to our problem. Though, the problem of scheduling tasks of home appliances have some peculiarities that cannot be seen in any other scheduling problem.

## II. System Model

We consider a set $P$ of *price signals*, $p_i$, from different transmission system operators (TSOs). Each price signal is a plot of the unit price of electricity per time. The price of electricity may be changed at the beginning of every hour. Having the ability to make a contract with a different TSO, the user may be subject to the minimum price signal, $p_{min}$, that is given by

$$p_{min}(t) = min\{p_i(t)\}$$

An example of a minimum price signal, $p_{min}$, is shown in Figure 1a.

Each task $J_i$ is specified by

- its earliest starting time (that is the current time unless specified by the user otherwise), $a_i$;
- its deadline, $d_i$;
- a boolean value, $pr_i$, representing whether the task is preemptable or not;
- a load power profile, $L_i$ that is is a task-specific curve that shows the power spent by the task during its non-preempted execution.

The load power profile is necessary for characterizing the tasks by representing the power drawn by each involved device for running the considered task. Figure 2a shows some tasks with their parameters. The load power profile for a washing machine depends on the set program, its duration and the water temperature chosen by the user. Limiting the energy characterization of the task to its average or total required energy would not be realistic in this domain.

We assume that there exists a set of local power micro-generators such as photovoltaics and wind mills. Due to the nature of these resources, the power generated by them varies with time; we assume that the energy taken from these sources is not billed to the users. We denote the total locally-generated power as $P_G(t)$ as shown in Figure 1b.

We define our problem according to the system model described above: given a task set $J$, a price signal set $P$, a locally-generated power $P_G$, and maximum allowed consumable power at any instant as $P_{max}$, the system must determine a schedule of the tasks such that the total cost for their execution is minimized. This problem needs to be solved every time a new task arrives (i.e., the user wants to start a new tasks). The scheduling is re-computed on the tasks not yet executed and on the remaining part of preemptable tasks. Non preemptable tasks that are being executed when the scheduler is run are considered as fixed; the available power is changed accordingly.

## III. The scheduling problem

Although the problem looks similar to a real-time operating systems scheduling problem with energy constraints, there are some differences. First of all, there is no shared device. Any task can be run in parallel as long as the total power drawn by the tasks does not exceed the electrical current capacity of the transmission cables. Moreover, scheduling theory from operating systems and operations research does not consider a mix of preemptable and non-preemptable tasks. In our case, for example, the washing machine task is non preemptable, but charging an electrical car is. In classical scheduling problems are tasks are either all preemptable or all non-preemptable.

We assume that minimum price signal, locally-generated power, and device power profile functions are piecewise constant with interval $T$. This assumption makes it possible to express them as a sequence of values. The time interval we are interested in for the scheduling problem is $[min(a_i), max(d_i)]$. Therefore $p_{min}[n]$ and $P_G[n]$ will be considered in this interval as a number sequence of length $N$, where $N$ can be computed as follows:

$$N = \frac{(max(d_i) - min(a_i))}{T}$$

Similarly, $L_i[n]$ is a sequence of length $N_L$ that can be computed as follows:

$$N_{L_i} = \frac{length(L_i)}{T}$$

The schedule for task $J_i$ can be represented as $s_i[n]$, a sequence of 0s and 1s, where 1 specifies that the task is to be run in the corresponding interval and 0 for otherwise. Such a formulation will allow us to express the scheduling as an optimization problem.

Power consumed by $J_i$ according to a schedule $s_i$ can be obtained by

$$P_i[j] = \begin{cases} L_i[\sum_{k=1}^{j} s_i[k]] & \text{if } s_i[j] = 1 \\ 0 & \text{otherwise} \end{cases}$$

For a given schedule, the total power consumption profile for all task can then be obtained by adding individual power consumption profiles:

$$P_{tot} = \sum_i P_i$$

By subtracting the power demand from the locally-generated power gives the power to be billed:

$$P_{billed} = P - P_G$$

We assume that the unused locally-generated power is not sold to the grid or stored. Therefore negative values in $P_{billed}$ are replaced with the value 0.

For a given price signal, the cost of the energy can be obtained with the scalar product:

$$C = P_{billed} \cdot p_{min} \cdot T$$

where $p_{min}$ and $T$ should be expressed in the same time unit (e.g. $T$ is in hours if $p_{min}$ is in €/kWh).

We identify $C$ as the objective function to be minimized. This minimization is subject to the following constraints:

- Tasks are scheduled to start after their earliest starting time:
$$\forall J_i : \qquad a_i \leq T \cdot min\{k : s_i[k] = 1\}$$
- Tasks are scheduled to finish before their deadlines:
$$\forall J_i : \qquad d_i - T \geq T \cdot max\{k : s_i[k] = 1\}$$
- Task $J_i$ is scheduled as many times as the length of its load power profile:
$$\sum_{k=1}^{N} s_i[k] = N_{L_i}$$
- If task $J_i$ is not preemptable, then it should be scheduled to run all at once:
$$pr_i = 0 \Rightarrow s_i(l) = 1$$
$$\text{for } l \in [min\{k : s_i(k) = 1\}, max\{k : s_i(k) = 1\}]$$
- At no time, the total power withdrawn by all tasks exceeds the allowed maximum, $P_{max}$.
$$P_{tot}[k] \leq P_{max} \qquad \text{for all } k$$

## IV. Use cases

The aforementioned system model and the scheduling problem can suit different scenarios. In particular, it can be used both to schedule tasks at individual home and at community level.

### A. Home level

In a private home, the controller schedules the household tasks with respect to the price signals and a local microgenerator (e.g., photovoltaic panels installed on the roof). The controller will keep all the information on tasks to be run locally and it will plan task execution for the householder.

### B. Community level

In a network of private homes, the controller schedules all the household tasks of the community with respect to the community-owned local generators such as wind mills and photovoltaic plants. This solution provides different advantages over the private home scheduling of tasks:

- better trading power;
- less communication/computation requirements on the infrastructure;
- less cost of the ICT infrastructure per home due to sharing;
- more predictable consumption at the community level;
- ability to impose peak demand response and balancing power policies at the community level.

Of course this solution is also subject to a number of disadvantages:

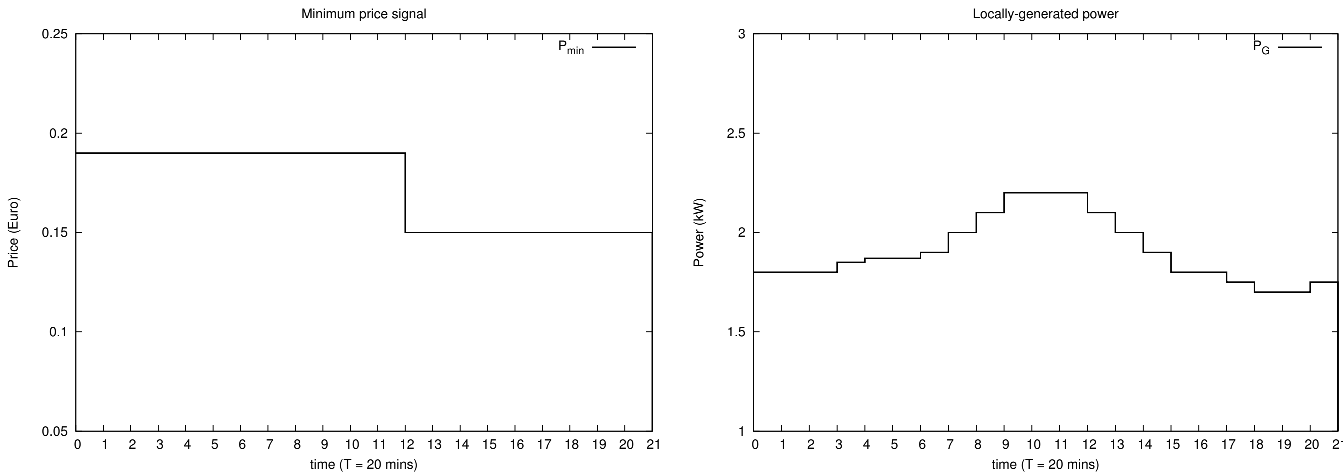
- privacy concerns due to making household tasks transparent to a shared controller;
- a community-level scheduling might provide less optimal results than home-level scheduling from the stand point of single users.

Proper solutions should be developed to overcome the aforementioned disadvantages and to exploit the advantages of this approach.

## V. Case Study

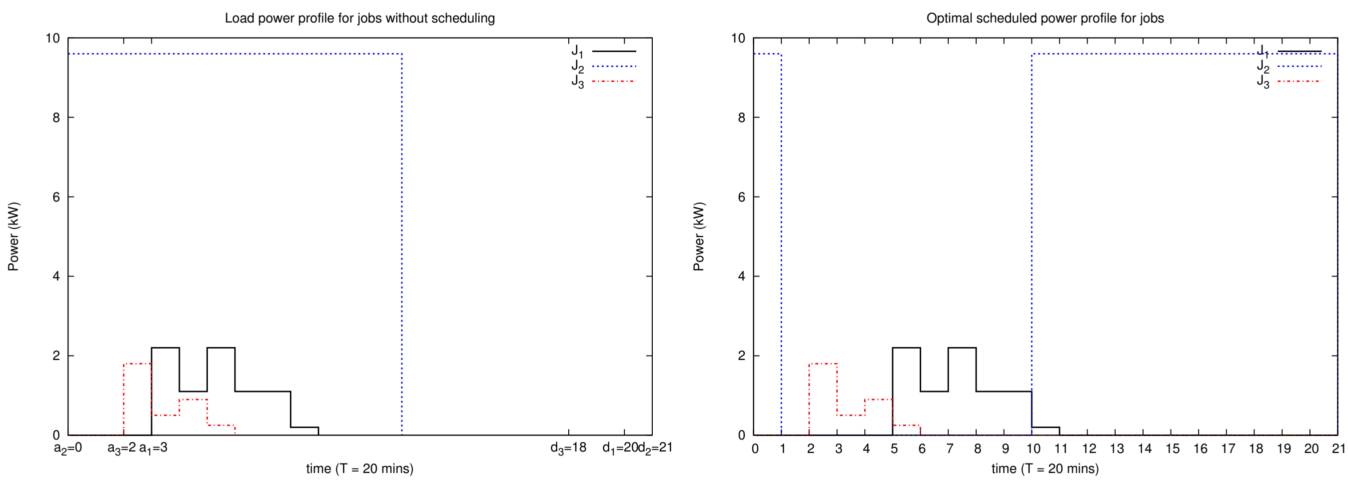
In this section we present a case study and we analyze the results obtained by applying our scheduler to the tasks with the goal of obtaining a cost saving by optimizing power consumption. The purpose of analyzing a case study is twofold: on one side we want to show how the electrical system would behave if the method proposed in this paper is adopted; on the other side we would like to show that, by scheduling the tasks correctly we could obtain a cost saving.

The case study that we considered is a normal house in a time span of 7 hours. In this time period we suppose that three activities are planned by the user. The first activity is a recharge of the batteries of an electric vehicle; the second activity is washing dishes by using a dishwasher; the third activity is using a washing machine. Table I summarizes the earliest starting times, the characteristics, and the deadlines for the different tasks. Tasks power profiles are shown in Figure




(a) (b)

Fig. 1: (a) Minimum price signal (b) Locally-generated power




(a) (b)

Fig. 2: (a) Load power profile for each task (b) Load profile with optimal scheduling

2a. Data related to the considered case studies are realistic: vehicle recharge data have been taken from the data of the Tesla car [7]; data for the washing machine correspond to the "cotton 95" program described in [8]; the dish washer power profile has been derived by the "cotton 60" profile of the same document. Total power consumption of the last two devices is in line with the power consumptions described in [9].

The vehicle recharging has been considered to be a pre-emptable task (i.e., it does not need to happen in subsequent instants of time); dish and clothes washing, on the opposite, have been considered to be non-preemptable tasks.

By considering the previous tasks and maximum allowed power consumption to be 15 kW, the optimal schedule has been computed by using combinatorial search. The search space was composed by 38,798,760 valid schedules. As can be noticed the search space is huge, even with a limited number of tasks and a limited time span. Our implementation of the exhaustive search executed in 35 minutes on Pentium Dual Core 1.8 GHz computer with 2 GB of RAM. This is the main problem associated with combinatorial search. A discussion on this topic is provided in Section VI.

Figure 2b shows the optimal schedule that has been obtained. The graph shows how the tasks have been scheduled to respect maximum power constraints and to provide the minimum possible cost for the user while respecting the

TABLE I: Earliest starting times, deadlines and characteristics of tasks.

| Task | earliest start | deadline | total duration |
|---|---|---|---|
| Clothes washing | 0:00 | 6:40 | 2h |
| Car recharge | 0:00 | 7:00 | 4h |
| Dish washing | 0:00 | 6:00 | 1h20' |

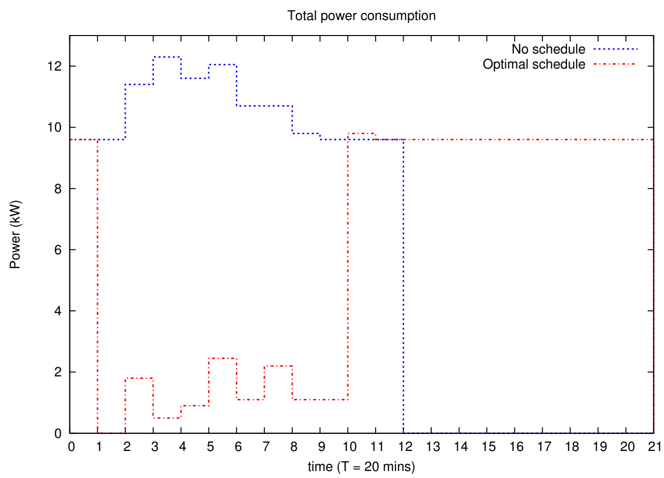



Fig. 3: Total consumed power for the cases of earliest and optimal scheduling

imposed deadlines. The car charging task is separated into two parts, one at the beginning and one after the completion of the other two non-preemptable tasks. The tasks are scheduled to use as much as possible locally-generated power, thus reducing costs for the user.

By scheduling the tasks optimally, in this case, we were able to reduce the cost about 23%: approximately €6.5 are necessary when tasks are scheduled as soon as the earliest starting time specified by the user arrives; €5.0 are necessary when tasks are scheduled optimally. Figure 3 shows the energy usage profiles obtained in the two cases. The graph shows how the optimal schedule better utilizes locally generated power and better exploits the flexibility of tasks for providing a cost saving.

## VI. Discussion

The problem that we describe in this paper is very complex and it has implications on how the electricity distribution system is organized; in this section we discuss some open topics; the discussion spans from the complexity of the scheduling algorithm to the management of locally-generated energy, passing by the requirements for new appliances and the home power supply network.

### *A. Scheduling Algorithm*

The problem of scheduling tasks in the home network is very complex as previously shown. In fact the worst case complexity of the combinatorial search is $\mathrm{O}(2^{MN})$ where $M$ is the number of tasks and $N$ is the number of time slots. Thus, solution time grows exponentially with the number of combinations considered. Solving this problem in a reasonable amount of time is already very difficult even on a powerful machine; it would be impossible on an embedded system. Therefore, some heuristics need to be developed to determine sub-optimal schedules in reasonable amounts of time. The heuristics considered need to be targeted to the computational power of the system considered and to the granularity of the schedule.

A further problem is given by the fact that energy available to each user is limited in each considered period of time. This, along with the deadlines set by the user, might lead to schedulability problems: the system might not be able to schedule one or more tasks in such a way that all the constraints (maximum power, deadlines) are satisfied. Though, the only constraint that can be physically violated is the deadline imposed by the user. Proper policies, customizable by users, should be defined for the case in which some tasks cannot be scheduled. Furthermore, an admittance test (i.e., a test that allows the system to quickly notify the user if a task cannot be accepted) should be developed. Currently we employ a weak schedulability test by comparing the maximum energy that can be drawn from the grid in the total duration of tasks to the total energy required to complete all tasks.

$$P_{max} \cdot N \geq \sum_i \sum_j L_i[j]$$

### *B. Home Appliances and Power Supply Network*

As previously mentioned, the power supply network has been undergoing a revision in the last years. The network will require some further adjustments to allow customers to perform short term negotiation of energy purchases: the energy sellers will need to implement finer grained mechanisms for energy pricing and, at the same time, they will need to provide price signals to customers. On the other side, customers will need to install suitable controllers in their buildings. These controllers should be able to read the price signals and to compute appropriate schedules for the tasks to be performed. To be able to use controllers in an effective way, home appliances will need to implement some new functionalities that will allow them to communicate with the controller and to expose the new capabilities to the users. Furthermore, the controllers will require the capability to communicate with the house metering device.

The development of interoperable embedded systems in order to enable above scenarios calls for the definition of communication standards: one for the communication between controllers and energy providers and another one for the communication among controllers, home appliances and the metering device. The definition of standards will allow multiple device and home appliance producers to design and sell compatible devices and, thus, it will boost the adoption of this technology.

### *C. Management of Locally-produced Energy*

Locally-produced energy can, in some periods of time, be in excess with respect to the user demand. In the model of the system presented in Section II we did not consider any specific option for this excess of energy. In the reality different options are available:

- store the energy in excess: energy might be stored, but this has a cost and it leads to some inefficiencies. In this case the impact on the model of the system that we are considering will be limited to the formula used to compute the price.

- Sell the energy in excess: by installing additional apparatus and by making suitable agreements with other parties, energy in excess can be sold. Also in this case, this will influence the price computation.
- Consume the energy in excess: energy can be used to perform tasks not directly requested by the user. For example, energy in excess could be used as an alternate way to heat water or to heat the house. Energy could also be used for useless tasks (i.e., wasted). If energy is used for alternate tasks, the price formula might be modified by considering the savings obtained by using the energy in excess. If the energy in excess, instead, is wasted, the formula used for computing the price does not require any modification.

### D. Distributed Management

As discussed in Section IV, task scheduling might be implemented both at single house level or in a distributed way. If each house has its own independent controller and all controllers follow the same policies, there might be cases in which all the houses (or a large part of them) schedule tasks in the same way. Thus, there might be undesired peaks in the total energy consumption. This side effect might be controlled both by using coordination and by using an appropriate pricing policy by the sellers. Some sort of coordination among distributed controllers can be used to influence task scheduling in such a way that not all houses schedule tasks in the same way. The pricing policy can be designed such that prices are dynamically dependent on the energy requests received for each period of time. In this way additional users might be discouraged in scheduling tasks for these periods and a strong peak demand might be avoided.

## VII. Conclusion & Future work

In this paper we propose a scheduling problem for household tasks that will help users in saving money spent for energy and that will allow energy producers to optimize their production processes. Our system model is based on the current and future trends for the electricity markets, smart grids and smart homes.

An important challenge is to create efficient scheduling algorithms that can be run on embedded systems. These algorithms must be efficient enough to be able to calculate the optimal schedule even for a large number of tasks and long time spans. As shown in this work, by using an exhaustive search, this is impossible even on a powerful machine such as a modern personal computer. We may resort to advanced optimization techniques such as constraint programming in order to obtain optimal results and better compare the performance of our heuristics.

Future work will focus on extending the system model to cover more of the real world cases. We assume price signals to be independently determined by the supplying companies. We may involve a negotiation phase where we can gain extra savings by extending the scheduler in such a way that it adjusts the load in order to increase its bargaining power. Similarly, we can extend the model with the ability to store and sell the energy when it is in excess.

## References


[1] K. Spees and L. B. Lave, "Demand response and electricity market efficiency," *The Electricity Journal*, vol. 20, no. 3, pp. 69–85, April 2007. [Online]. Available: http://ideas.repec.org/a/eee/jelect/v20y2007i3p69-85.html

[2] A. Eßer, M. Franke, A. Kamper, and D. Möst, "Future power markets - impacts of consumer response and dynamic retail prices on electricity markets," *Wirtschaftsinformatik*, vol. 49, no. 5, pp. 35–41, 2007.

[3] S. Borenstein and S. P. Holland, "On the efficiency of competitive electricity markets with time-invariant retail prices," National Bureau of Economic Research, Working Paper 9922, August 2003. [Online]. Available: http://www.nber.org/papers/w9922

[4] R. Janssen, "Towards energy efficient buildings in Europe," The European Alliance of Companies for Energy Efficiency in Buildings (EuroACE), June 2004.

[5] A. Eßer, A. Kamper, M. Franke, D. Möst, and O. Rentz, "Scheduling of electrical household appliances with price signals," in *OR*, K.-H. Waldmann and U. M. Stocker, Eds., 2006, pp. 253–258.

[6] C. Moser, D. Brunelli, L. Thiele, and L. Benini, "Real-time scheduling for energy harvesting sensor nodes," *Real-Time Systems*, vol. 37, no. 3, pp. 233–260, 2007.

[7] Tesla motors. [Online]. Available: http://www.teslamotors.com

[8] Washing machine: Instructions for use. [Online]. Available: http://products.gorenje.si/fts/GetDigitDoc.aspx?sifra=161108&jezik=en&t%ipVsebine=1&docName=161478en%2Epdf

[9] Power consumption table. [Online]. Available: http://www.absak.com/library/power-consumption-table