Chapter 12

Energy Demand Management Through Uncertain Data Forecasting: An Hybrid Approach

M. Severini, S. Squartini and F. Piazza

Abstract  Although Smart Grids may represent the solution to the limits of nowadays Power Grid, the turnover may not occur in the next future yet due the complex nature of energy distribution. Thus, as a more short term effort, to improve the responsiveness of the energy demand to the power grid load, more and more energy providers apply dynamic pricing schemes for grid users. Believing that dynamic pricing policies may be an effective asset even at a micro-grid level, an hybrid energy management scheme is proposed in this contribution. While the nonlinear nature of a micro grid, involving the task allocation and the thermal constraint satisfaction, can be modeled as a mixed integer nonlinear programming problem, neural-network forecasting abilities can provide a sustainable support under realistic operating conditions. Based on the forecast of solar energy production and grid energy prices and outdoor temperature, the optimization of tasks allocation is aimed to lower both the user costs and the grid burden while accounting the thermal comfort of the user. Through computer simulations, whose degree of realism is enhanced by the adoption of forecast data, the shift of the grid load towards low energy price hours is confirmed.

12.1 Introduction

Smart Grids are reckoned to be the next generation power grid technology, intended to overcome many limits of nowadays infrastructures [Cecati et al. (2010); Ipakchi and Albuyeh (2009)]. In fact, with the assistance of information technology and automatic routing of power, they provide the means to improve energy distribution. While this technology may provide a major step ahead in power distribution, production and consumption may also require attention. In fact, electrical energy storage is not a solution able to support power distribution, to maintain the power parameters within standards energy production must always match the consumption. This requirement, in turn, affects the energy market, which therefore requires
a specially strict regulation.

To overcome this limit several solutions are nowadays object of research. The most active seem to focus on distributed storage through grid connected electrical vehicles [Liu et al. (2013); Saber and Venayagamoorthy (2012); Venayagamoorthy (2011)] and demand response [Chapman et al. (2013); Wang et al. (2013); Chakrabarti et al. (2012)].

The former, while appealing and promising, still does not account two major aspect of the energy storage. The first one is the efficiency of the storage system. In fact, even though in an highly efficient system conversion losses may be lower than 5%, on a large scale system they can easily amount to the order of mega watt hours per day. The second aspect is the life expectation of the energy storage itself. Since charge and discharge shorten a battery life, grid connected electrical vehicles may most likely require early battery replacement. Therefore a grid connected vehicle solution may be unappealing to the owners of the vehicle, and may prevent them to include their vehicle in the storage pool.

The latter approach, also quite interesting, promotes the regulation of the electricity demand through prices. It relies however on the user, and requires consumer profiling [Ghosh et al. (2012)], data disaggregation [Makonin et al. (2013)] and so on. While it may still too early to draw conclusion, the reliance on the end user may not lead to the expected performances.

In the authors’ opinion, a more promising solution, is represented by Micro Grids [Kirthiga et al. (2013)]. While micro grids, ma may also represent the next evolutionary step of power grids, they may also lead the demand response approach to the next level. By accounting production and consumption within the power grid, the entire energy flow can be managed as a whole, improving efficiency reliance, and reducing the need of energy storage systems.

In this perspective, domestic tasks and energy management [Squartini et al. (2013b)], may have a major role, since it can respond automatically to a dynamic pricing scheme. While it can also account local energy storage and production, its strong point is the ability to manage the energy consumption in a transparent way with respect to the user.

On a large scale therefore, such approach may provide the means to regulate the energy demand over the grid. As such, not only the energy balance across the grid can be maintained more efficiently, but also a less strictly regulated energy market may be possible. Also, although electrical vehicles may still be an integral part of the domestic energy management, the storage included in domestic solar power plants may be used instead, with less costs, since it is already part of the plant, and more efficiency, since it is used as extrema ratio.

Obviously enough, the automation of domestic tasks, being also a process transparent to the user, is an highly constrained decisional problem. Therefore, among the available solving techniques [De Angelis et al. (2013a); Squartini et al. (2013a)], many, such as Particle Swarm Optimization (PSO) [Soares et al. (in press)], Fuzzy
Logic [Cui and Dai (2011)], Adaptive Dynamic Programming [Fuselli et al. (2013, 2012); Boaro et al. (2013)] but also Linear Programming [Tham and Luo (in press)], have been deemed not particularly suited to deal with the task scheduling, whereas Mixed Integer Programming ones [Bozchalui and Sharma (2012); De Angelis et al. (2013b); Nagasaka et al. (2012)] have shown to be quite promising.

As in our previous work [Severini et al. (2013)], extending the concept of task automation, although not strictly a task, the thermal management of the domestic environment is accounted. On purpose, the thermal behaviour of the domestic environment is modelled by means of the European standards [ISO (2003, 2007a,b)]. Due to the highly nonlinear nature of the problem, a mixed computational scheme, combining a genetic algorithm (GA) and a deterministic minimization approach, is used to apply the thermal requirement of the user and compute the energy demand of the environment.

The resulting report is integrated within the energy balance and a MILP problem, modelling the energy management, is implemented to select the optimal task schedule. An hybrid computational approach, mixing deterministic and heuristic computing technique is therefore employed to minimize the energy bill through optimal scheduling.

In the present work data uncertainty is also included [Ciabattoni et al. (2013a,b)]. In order to select the optimal execution time table for the assigned tasks, the knowledge of the future values of the scheduling parameters is a key factor. However, data uncertainty may lead to sub-optimal results. To evaluate this aspect a few predictors, based on Artificial Neural Networks [Hernandez et al. (2013)], are implemented to provide a day ahead forecast of solar irradiation, outdoor temperature and electricity price.

The model at the core of the task scheduling and energy cost minimization is presented in Section 12.2, whereas in Section 12.3 the thermal model at the base of the heating/cooling system is proposed. The forecasters are described in Section 12.4. In Section 12.5 a brief overview on the solving algorithm part of the framework is reported. In Section 12.6 the simulated scenario is presented and the simulation results are discussed. Section 12.7 draws the work conclusions.

12.2 Home Energy Management Problem: the Model

The purpose of automated task scheduling is the selection of an optimal time table, so that the tasks are executed within the time frame provided by the user, while lowering the energy bill to its minimum. Since the energy price rise when the energy demand increase, the optimal time table will most likely contain the energy purchase during peak hours, thus shaping the energy demand of the building. In this perspective, a dynamic pricing scheme may provide an almost real-time feedback to the scheduler. On a large scale, not only the energy cost is contained, but even the grid burden can be equalized over the daily time frame.
Clearly, if the thermal regulation is accounted, since the thermal comfort is not supposed to depend on the energy price, the energy demand of the heat pump cannot be regulated on a price basis. However, if local energy storage and production are available, some sort of demand shaping may still be possible. In conclusion, to adjust the energy demand of the building, the scheduling problem can be modelled by evaluating the monetary balance of energy consumption and production. In the following:

\[
Q = \sum_{t=1}^{\text{slots}} \left\{ \sum_{j=1}^{\text{houses}} \sum_{i=1}^{\text{tasks}} (E_{j,i} \cdot t_{b_{j,i,t}}) + (E_{i}^{c} - E_{i}^{d}) \right. \\
- E_{t}^{re} + E_{t}^{so} + E_{t}^{he} \left. \right] C_{t} + \left. \left( -E_{t}^{so} \cdot \text{price}_{t} \right) \right\} \tag{12.2.1}
\]

\(t_{b_{j,i,t}}\) is the task binary variable that defines the activity state (ON/OFF) of the \(i\)-th task of \(j\)-th building during the \(t\)-th time slot. The variable \(E_{j,i}\) represents the energy demand of the \(i\)-th task of \(j\)-th building in each time slot. Therefore the sum over \(i\) and \(j\) index returns the total energy demand of the assigned tasks at the \(t\)-th time slot. The amount \((E_{i}^{c} - E_{i}^{d})\) represents the energy transferred to or from the storage at the \(t\)-th time slot, while \(E_{t}^{re}\) is the renewable energy production, \(E_{t}^{so}\) accounts the sold energy amount and \(E_{t}^{he}\) describes the heater energy demand. Therefore the quantity within brackets accounts the net energy demand at each time slot. On the other hand, since \(C_{t}\) represents the energy purchase price at the \(t\)-th time slot, the amount within braces describes the total energy cost minus the total energy income at each time slot, that is the energy balance at the \(t\)-th time slot.

Said monetary balance shall be complemented by the constraints binding together the unknowns of the equation, that have been already presented in our previous work [Severini et al. (2013)].

12.3 Modelling the Thermal Optimization Sub-problem

Since the thermal regulation is not affected by the energy price, it may be more convenient to address this aspect as a separate problem. The core of the thermal regulation system is an heat pump. Since this matter has been already discussed in a previous work [Severini et al. (2013)], it will only be presented briefly.

12.3.1 Notation

Indices:

\(t\) time slot index
\(j\) house index
\(k\) room index
Parameters

- **surf**: number of surfaces of the house thermal model
- **$E_t^{he}$**: electrical energy demand at the t-th time slot
- **$P_{j,k,t}^t$**: thermal power at the t-th time slot to the k-th room of the j-th building
- **$P_t^t$**: thermal power at the t-th time slot (single room case)
- **$\Delta$**: time slot duration (in hours)
- **$\theta_{hp}$**: heat pump output temperature ($^\circ$C)
- **$\theta_i$**: indoor temperature ($^\circ$C)
- **$\theta_o$**: outdoor temperature ($^\circ$C)
- **$\theta_t(t)$**: target temperature at the t-th time slot ($^\circ$C)
- **$\varepsilon$**: temperature tolerance (0.5) ($^\circ$C)
- **$c_p$**: air heat capacity at NTP
- **$M_{air}$**: air mass in the house (Kg)
- **$k_l$**: house heat loss factor (W/$^\circ$C)

### 12.3.2 Heat pump constraints

The electrical energy, required at each time slot, is obtained as the thermal energy, required by each room in the same time frame, on the Coefficient of Performance (COP) of the heat pump when heating, whereas the Energy Efficiency Ratio (EER) is used if cooling:

$$E_t^{he} = \frac{1}{\text{COP}} \sum_{j=1}^{\text{houses}} \sum_{k=1}^{\text{rooms}} (\Delta P_{j,k,t}^t) \quad \forall t : t = 1, \ldots, \text{slots}. \quad (12.3.1)$$

On the other hand, the thermal power $P_{j,k,t}^t$ of the k-th room of the j-th building at the t-th time slot is the amount that satisfies the temperature constraints. These constraints are defined with the heat balance of the buildings at its base [Kazanavičius *et al.* (2006); Qela and Mouftah (2010); Fux *et al.* (2012)]. If the overdot notation is used to represent the time derivative, the heat fluxes can be defined as:

$$\dot{Q}_{hp} = P_t^t c_p (\theta_{hp} - \theta_i) \quad (12.3.2)$$
$$\dot{Q}_{loss} = k_l (\theta_i - \theta_o) \quad (12.3.3)$$

where (12.3.2) expresses the thermal energy provided by the heat pump, while (12.3.3) represents the thermal energy escaping through the walls. On the other
hand, the indoor temperature variation, over time, can be calculated as the net
heat flux on the thermal capacity of the air mass inside the room, which leads to
the following:

\[
\dot{\theta}_i = \frac{1}{M_{\text{air}}c_p} (Q_{hp} - Q_{loss}). \tag{12.3.4}
\]

To account the discrete time domain required by the scheduler, (12.3.4) can be
rewritten as a difference equation:

\[
\theta_i(t+1) = \theta_i(t) + \Delta \frac{P_{th} c_p}{M_{\text{air}}c_p} (\theta_{hp} - \theta_i(t)) - k_i(\theta_i(t) - \theta_o(t)) \tag{12.3.5}
\]

being \( t \) the discrete time variable. By algebraic manipulation the temperature is
then be expressed as:

\[
\theta_i(t+1) = \theta_i(t) \left[ 1 - \frac{P_{th} \Delta}{M_{\text{air}}c_p} - \frac{k_i \Delta}{M_{\text{air}}c_p} \right] + \frac{P_{th} \theta_{hp}}{M_{\text{air}}c_p} + \frac{k_i \theta_o(t)}{M_{\text{air}}c_p} \tag{12.3.6}
\]

leading to the representation of the indoor temperature as a function of thermal
fluxes, indoor temperature, and outdoor temperature in the previous time slot. On
the other hand, the constraints set is obtained by requiring that

\[
\forall t : t = 1, \ldots, \text{slots} \\
\theta_i(t) - \varepsilon \leq \theta_i(t) \leq \theta_i(t) + \varepsilon. \tag{12.3.7}
\]

The coefficients \( M_{\text{air}} \) and \( k_i \), that appear in the equations, represent, respectively, the air mass within each room and the heat loss factor of each room. Their
value are obtained by means of a simple building geometry accounting several rooms.
Regarding \( k_i \) it is worth to mention that its value is estimated in accordance to the
EN 12831, EN ISO 13370, EN ISO 13789 standards. This matter will be discussed
in Section 12.6.

12.4 Neural Networks for Uncertain Data Forecasting

In order to compute the energy balance, the information concerning energy price,
solar production and outdoor temperature is required. Therefore, to select the
optimal time table to be applied in the future, information on the future values of
energy price, solar production and outdoor temperature shall be used.

Although forecast data can be retrieved from many providers, such as weather
forecast services and independent system operators, the prediction error and its
effect on the scheduling process are to be taken into account. On purpose, to better
assess the prediction error, for each of the required information set a forecaster
has been developed. Since absolute prediction accuracy is now paramount in the
current work, the implementation has been designed with forecaster simplicity in mind.

In particular, by means of the Neural Network toolbox, provided by the MathWorks MatLab\textsuperscript{1} framework, three multi-layered perceptrons (MLP) have been used as forecaster. The neural networks training is carried out over a data set covering two years, namely 2009 and 2010. The National Climatic Data Center\textsuperscript{2} (NCDC) has been selected for the meteorological records, whereas the ISO of New England\textsuperscript{3} (ISO-NE) provided information about the energy price.

The three forecaster share the same MLP structure: 49 neurons are used in the input layer, 48 in the hidden layer and 24 in the output layer. For every neuron the hyperbolic tangent is used as activation function. A day ahead prediction approach is used, thus 24 samples, one per hour, are generated at a time from the samples of the previous day. The data normalization is left to the toolbox and it maps the input to the interval [-1, 1]. The performance function of choice is the Mean Absolute Error (MAE). To reduce the training time, given the number of neurons, the gradient descent with momentum and adaptive learning rate is used. To avoid a premature completion of the training process, the number of validation check is fixed equal to 500, and the number of epoch has been increased accordingly.

Concerning temperature and irradiation forecasting, for each predicted set, the input data is represented by the 24 temperature hourly samples, the 24 solar irradiation hourly samples, and the day index within the year, which is coded through the minus cosine function. Regarding the price forecast, on the other hand, the energy price hourly samples are used as input in place of the solar irradiation hourly samples. The temperature samples are still used as input in this case. Clearly, since the output data is composed by 24 samples representing the hourly data of the next day, recurring prediction and error propagation have been avoided.

Given the simple structure of the network and its input set, the prediction accuracy is usually high if little to no changes are recorded from a day to the next. On the other hand, when highly variable conditions are encountered, the prediction accuracy drops. In this regard, even though a deep analysis of the results has not been carried out, a simple evaluation reveals that a proper data preprocessing would greatly improve the performance of the forecaster. Additionally, the nature of the forecast error appears to be systemic, and probably due to the lack of input data. As a result, the performance is not on par with the performance of the state of the art. Nonetheless the obtained forecast provides an ample set of cases, that are more than adequate to test the error propagation through the scheduler. In a real life scenario, an accurate predictor would be mandatory. As such, the improvement of the forecaster issues will be addressed in future works.

\begin{footnotesize}
\begin{itemize}
\item \textsuperscript{1}http://www.mathworks.com
\item \textsuperscript{2}http://www1.ncdc.noaa.gov
\item \textsuperscript{3}http://www1.ncdc.noaa.gov/pub/data/nsrdb-solar/station-data-2010/
\item http://www.iso-ne.com/aboutiso/index.html
\item http://www.iso-ne.com/markets/hstdata/hourly/index.html
\end{itemize}
\end{footnotesize}
12.5 Optimization Algorithms

By means of the suggested objective function and constraints, the scenario of interest is modelled. Based on historical data, the forecast of outdoor temperature, solar irradiation and energy prices are generated by means of three ANN forecaster.

Whether forecast or historical data are used, energy prices are directly assigned to the model. Solar irradiation values are used to compute the energy production of the solar power plant, whereas the outdoor temperature is used to compute the energy demand of the heat pump through the thermal model.

For instance, the thermal load model is instantiated and by means of the outdoor temperature the energy demand of the heat pump is computed. This information is then integrated with the solar energy production and the energy rates to provide the input to the energy balance model. Then the main sub problem, implementing the energy balance, is instantiated.

After the model instantiation and set up, the MILP problem is generated and the MILP solver is invoked. At the end of the solving routine the task time table and the expected energy monetary balance are obtained. The resulting algorithmic framework is presented in Fig. 12.1.

The first step is represented by the data input assignment, in which the scenario configuration is set up. Then, the sub-problem focused on the heat pump energy demand is formulated.

The next step requires to integrate the main scheduling sub-problem, involving the task scheduling and the energy management, with the heat pump energy demand, thus a MILP problem, modelling the energy monetary balance, is obtained. The main programming problem is then solved to obtain the optimal task and the energy resource schedule.

After the time table is retrieved, if said time table is based on forecast data, the same framework is used as a simulator to compute the actual energy balance resulting from the task execution and energy management. In contrast, in the search phase, the returned energy balance is the expected, or predicted one. In other words the two balances coincide if the prediction error is zero, but they differ when a prediction error occurs.

To run the framework as a simulator, the forecast data is replaced by the corresponding historical data, and the time table obtained in the previous phase is assigned as an input. The framework, running as a simulator, computes the activity of the energy storage, the energy production and consumption, and therefore computes the electricity balance based on the historical data and the provided task schedule.
Energy Demand Management Through Uncertain Data Forecasting: an Hybrid Approach

Problem Assignment:
- Solar Data Forecast
- Electricity Price Forecast
- Outdoor Temperature Forecast
- Input Data Computation

Thermal Load Subproblem Modelling
(as NLP problem)

Heat pump energy demand computing

Energy monetary balance
(as MILP problem)

Task optimal schedule search

Exit

Fig. 12.1 Algorithmic Framework flow chart.

12.6 Smart Home Energy Management: Case Studies and Simulation Results

The scheduling process is carried out by means of the MatLab environment. The MILP solver, namely GLPK, is invoked through the Opti Toolbox4 for MatLab. The Hybrid Genetic Algorithm and the Artificial Neural Networks, on the other hand, are part of their respective toolboxes provided by Mathworks. The framework is hosted by a Laptop PC based on the Intel Core i7 CPU series, with 8GB of ram, running on the Microsoft Windows 8 64-bit OS.

12.6.1 Thermal model characterization

To properly evaluate the performance of the thermal regulation, a simple building structure is employed as a target. While the structure is simplified enough to reduce the complexity of the model, the characterization is based on the European Standards EN 12831:2003, EN 13370:2007 and EN 13789:2007, so that all the most

4http://www.i2c2.aut.ac.nz/Wiki/OPTI/index.php/Main/HomePage
important thermal loss contributions are included.

A schematic representation of the building is reported in Fig. 12.2.

![Building model schematic representation](image_url)

The building parameters are shown in Table 12.1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Building’s length</td>
<td>25</td>
<td>m</td>
</tr>
<tr>
<td>Building’s width</td>
<td>10</td>
<td>m</td>
</tr>
<tr>
<td>Rooms’ length</td>
<td>12.2</td>
<td>m</td>
</tr>
<tr>
<td>Rooms’ width</td>
<td>4.7</td>
<td>m</td>
</tr>
<tr>
<td>Building’s height</td>
<td>4</td>
<td>m</td>
</tr>
<tr>
<td>Roof’s pitch</td>
<td>35°</td>
<td></td>
</tr>
<tr>
<td>Windows’ count</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Windows’ height</td>
<td>1</td>
<td>m</td>
</tr>
<tr>
<td>Windows’ width</td>
<td>1</td>
<td>m</td>
</tr>
<tr>
<td>Windows’ thickness</td>
<td>0.005</td>
<td>m</td>
</tr>
<tr>
<td>Walls’ thickness</td>
<td>0.2</td>
<td>m</td>
</tr>
<tr>
<td>Slab on grade thickness</td>
<td>0.3</td>
<td>m</td>
</tr>
<tr>
<td>Windows’ thermal conductivity</td>
<td>0.78</td>
<td>W/(m²·°C)</td>
</tr>
<tr>
<td>Walls’ thermal conductivity</td>
<td>0.30</td>
<td>W/(m²·°C)</td>
</tr>
<tr>
<td>Slab on grade thermal conductivity</td>
<td>0.82</td>
<td>W/(m²·°C)</td>
</tr>
</tbody>
</table>

This set of parameters and the air density at NTP (1.204 kg/m³) are used to compute the air mass within each room, referred as $M_{air}$ in the model description in Section 12.3. The parameter referred as $k_l$ that is, the heat loss factor, is computed accordingly to the procedure stated in the aforementioned European Standards.
Concerning the heat pump, a 6 kW device is used. The COP factor is equal to 3.4 whereas the EER factor is chosen equal to 3. In the current scenario the outdoor temperature spans from about 15 °C to about 35 °C, thus no additional adjustment to either the COP or the EER is deemed necessary. The output temperature of the heat pump is assumed equal to 50 °C when heating, and equal to 10 °C when cooling. The heat pump is assumed able to switch from heating to cooling and vice versa depending on the outdoor temperature.

In order to compute the energy demand of the thermal regulation process, the MatLab GA solver setup assumes a population size limited to 20 candidates, a generation stall limited to 10, whereas the tolerance is set to $1E^{-10}$, the mutation function is set to @mutationadaptfeasible and the hybrid function is set to @fmincon. The genetic algorithm is therefore used to locate the area around the global minimum, whereas the fmincon operator locates the actual minimum within that area, improving the convergence time of the algorithm.

12.6.2 Task scheduling and energy cost accounting

The scheduling interval spans over a time frame of 24 hours, and requires the management of a set of appliances composed by a washing machine, a drying machine, a oven and a dish washer. The TV is also considered in the scenario. The tasks are described in Table 12.2.

<table>
<thead>
<tr>
<th></th>
<th>Allowed time window</th>
<th>Forbidden time window</th>
<th>Tasks</th>
<th>Energy Demand</th>
<th>Master ID</th>
<th>Duration (Hrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Washing machine</td>
<td>Begin 8:00</td>
<td>End 22:00</td>
<td>Begin 14:00</td>
<td>End 16:00</td>
<td>3</td>
<td>800 task 1 - 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1000 task 2 task 1 1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>900 task 3 task 2 1</td>
</tr>
<tr>
<td>Drying Machine</td>
<td>Begin 8:00</td>
<td>End 22:00</td>
<td>Begin 14:00</td>
<td>End 16:00</td>
<td>1</td>
<td>2500 task 4 task 3 2</td>
</tr>
<tr>
<td>Oven</td>
<td>Begin 10:00</td>
<td>End 13:00</td>
<td>1</td>
<td>2000 task 5</td>
<td>-</td>
<td>2</td>
</tr>
<tr>
<td>Dishwasher</td>
<td>Begin 14:00</td>
<td>End 22:00</td>
<td>3</td>
<td>800 task 6</td>
<td>-</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1000 task 7 task 6 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>500 task 8 task 7 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TV</td>
<td>Begin 8:00</td>
<td>End 18:00</td>
<td>1</td>
<td>100 task 9</td>
<td>-</td>
<td>10</td>
</tr>
</tbody>
</table>

Regarding the storage system, a single set of batteries is considered. The parameters are reported in Table 12.3.

<table>
<thead>
<tr>
<th>$\eta_c$</th>
<th>$\eta_d$</th>
<th>$Chl^{MIN}$</th>
<th>$Chl^{MAX}$</th>
<th>$P_{c}^{MAX}$</th>
<th>$P_{d}^{MAX}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>kWh</td>
<td>kW</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.85</td>
<td>0.85</td>
<td>1</td>
<td>5</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>
Concerning the energy rates, a dynamic pricing scheme is emulated by mean of either historical or forecast market prices. On this regards, since the values refers to the wholesale locational marginal price, whereas the retail price includes taxes and ancillary costs, to obtain a realistic retail price, a multiplicative factor of ten is also accounted. As a result, in the current scenario, the retail energy price is assumed to be ten times the wholesale price. In the same scenario, the energy selling price has been assumed equal to 1 $cent per kWh.

12.6.3 Solar production

The current simulation scenario assumes a solar power plant as part of the domestic environment, its panel area being 20 squared meters, and its efficiency index being equal to 20%. As previously stated, the energy production is computed using the hourly solar irradiance as an input.

12.6.4 Data forecasting

To evaluate the scheduling framework performance, a forecast data set is used as an input to the scheduler. Although the forecast time frame spans over almost two years, which allowed several tests to be carried out, only the forecasts corresponding to a few days are presented in the current manuscript as a sample.

Also, to evaluate the forecast accuracy in a normalized fashion, for each day, the MAE of the forecast, against the corresponding historical data, is divided by the absolute mean value of the historical data. This approach has been devised to avoid the issues, due to negative and null values, that usually affect the Mean Absolute Percentage Error (MAPE).

This characterization was used to select three forecast set of samples. The set are referred to as “day 1” (02/05/2010), “day 2” (10/08/2010) and “day 3” (24/09/2010). The normalized MAE for these forecasts lies, respectively in the intervals [0, 0.1], (0.1, 0.2] and (0.2, 0.3].

In Figures 12.3, 12.4 and 12.5, the input data profiles corresponding, respectively, to solar energy production, outdoor temperature and energy prices, are presented comparing the forecast data against the historical counterpart for each of the selected days.

12.6.5 Energy management performance

The suggested set-up is used to evaluate the framework performance. By means of the data forecast, a task time table is computed. Under these circumstances, the expected energy demand of the heat pump is the amount computed using the outdoor temperature forecast, whereas the expected energy production is computed with the solar irradiance forecast as a basis. After the time table is retrieved, the framework is used as a simulator. The returned energy monetary balance, which
results from the execution of the task, accounts the actual energy demand of the heat pump, the actual energy production and the actual prices, thus it provides the actual energy cost, rather than the expected one. Since the forecast always include a prediction error, the result is almost certainly sub optimal, thus said result will be addressed as “Sub Optimal” in the reported plots and figures.

The performance reference is obtained from an ideal case that assumes an exact prediction as possible. Whenever the prediction error can be considered equal to zero, the data forecast will match the historical counterpart. In this scenario, then, it is possible to search for the task time table using the historical data rather than the forecast counterpart. As a result, the actual energy monetary balance obtained through simulation will match the expected cost, computed by the framework during
the search of the task time table. As such, since the algorithm will provide the time table that minimize the energy cost, the optimal result is obtained. For this reason, the obtained result will be referred to as “Optimal” in the reported plot and figures.

The comparison of optimal and sub optimal results will provide the means to evaluate the relationship, between prediction error and scheduling performance, in term of energy net cost.

An additional reference case, addressed as “baseline scenario”, consists of a domestic environment, without any energy management feature, nor energy storage facility and without task scheduling abilities. In this environment the energy produced by the solar power plant is sold directly to the main grid, whereas the tasks are executed in the first available time slot. A time slot is assumed to be available if it falls within the time frame given to the task and if the task can be executed without exceeding the maximum power allowed by the building wirings. For this scenario no plot will be presented.

Concerning the realism of the scenario two aspects shall be accounted. The first one is related to the assumption that, within the environment, the thermal regulation depends on a thermostat. The thermal model, provided by the framework, is only meant to compute the energy demand. If historical data is used an input, the actual energy demand will be obtained. If forecast data is used instead, the expected energy demand is obtained.

The second aspect pertains the realism of the thermal regulation. In order to evaluate the framework performance, a strict thermal regulation is used to enforce the heat pump activity. In real life however, thermal regulation is usually not used all year around, thus a certain degree of realism is discarded in the current work.

The first test to be carried out is based on the data set referred to as “day 1”. The error prediction of the data forecast, within this set, is less then 10%. As said, first the energy demand of the heat pump is computed. This routine depends on the
outdoor temperature, the thermal constraints and the building thermal behaviour. For the optimal case, the temperature profile is reported in Fig. 12.6, whereas for the sub-optimal case the resulting indoor profile is reported in Fig. 12.7. By comparing the two, the effect of the prediction error is clear. The difference becomes even more apparent if the energy demand, reported in Fig. 12.8, is evaluated.

![Fig. 12.6 Data set “day 1”: Room temperature profile against outdoor temperature and constraints](image)

![Fig. 12.7 Data set “day 1”: Room temperature profile against forecast outdoor temperature and constraints](image)

The comparison of the profiles highlights that the effects of the prediction error highly depend on the temperature constraints. Since no thermal regulation is required without thermal constraints, the prediction error is unable to propagate during the time slots where temperature requirements are not assigned. Also, the
indoor temperature is bound to follow the outdoor temperature, and the thermal regulation is only required to maintain the indoor temperature within the given range. Therefore, if both the outdoor temperature and the corresponding forecast profile fall into the assigned range, no regulation will be necessary, thus the prediction error will not propagate. In the current scenario, a 1 °C temperature range was chosen, thus the error propagation occurs, if a wider range where to be chosen, however a different situation may present itself.

Recalling that the task scheduling process accounts the heat pump activity, the energy price and local production, it is also possible to conclude that the prediction error, originating from the outdoor temperature forecast, affects the time table indirectly, whereas the prediction errors originating from both the solar irradiation and electricity price forecasts operate directly. On this subject, while a few educated guesses can be made in very specific cases, a general model of the interaction among the prediction errors does not exists. Due to their stochastic nature, in fact, it is not possible to assess beforehand the error amount, moreover in each time slot. In turn then the interaction among error, that is if the errors sum up or cancel each other out, is not known.

Although, from a general point of view, the way the task time table is distorted by the prediction errors is not predictable, it should also be noted that the time slot allocation is also subject to the system constraints. The maximum power allowed by the house wirings shall be accounted, and thus the fact that the number of tasks that can be executed at once is limited. The sequential nature of the task is also to be considered, and thus the fact that the tasks cannot be executed in any order. In addition, it shall be noted that each task has a given time frame. In other words, the robustness of the scheduling process, with respect to prediction errors, may increase the more tasks are to be scheduled, since the degrees of freedom of the allocation process are reduced. Nonetheless, it shall also be observed that, when
energy demanding tasks are involved, even slightly distorted time schedule may lead to significant performance drop.

For instance, if the optimal time schedule, reported in Fig. 12.9, is to be compared to the sub-optimal time schedule, reported in Fig. 12.10, it is possible to observe that only the entries marked as “Task 3” and “Task 8” are actually affected by the forecast error.

By simulating the task execution using the computed task schedule, the actual energy management profiles can be evaluated. Concerning the reference case, being optimal, the energy allocation produce the minimum energy cost. When the sub optimal case is considered, obviously, a less efficient result is achieved. It may
also worth to mention, in this case, that since the optimal case, being optimal, guarantees the best achievable performance, the sub optimal setup can, at most, achieve the same result. That is, under no circumstances better performances can be achieved.

Concerning the energy costs, reported in Fig. 12.11, the “Optimal” entry produces a total energy cost of 0.21$, whereas the “Sub Optimal” counterpart leads to a total energy cost of 0.29$. Concerning the energy income, reported in Fig. 12.12, the total income of 0.1$ is obtained in both cases. The energy minimum net cost (reference case) is thus 0.106$, the expected net cost for the forecast case is 0.69$, whereas the actual net cost for the forecast case is 0.19$.

Also the stored energy level can be evaluated (Fig. 12.13), and a better insight of the scheduling process can be gained. In particular, after 20.00 the battery is fully charged, meaning that the different slope in the energy cost plots, after 20.00, only depends on the task allocation. Also, at 8.00 the optimal time schedule allows the battery to recharge to full level, whereas the sub optimal time table prevent the recharging phase till 10.00 and requires an additional discharge at 13.00, thus increasing the battery stress.

As a further mean of comparison, for a baseline scenario, the energy cost will amount to 5.31$, whereas the energy income would amount to 0.34$. The net energy cost will amount to 4.97$ meaning that the optimal case net cost will amount to 2.1% of the baseline net cost, whereas the sub-optimal net energy cost will amount to 3.8% of the baseline net cost.

By evaluating the scheduling process by means of the “day 3” set-up, a prediction error higher than 20% and lower than 30% will be accounted. Similarly to the previous case, concerning the heat pump expected energy demand, the forecast case will differ from the reference case (Fig. 12.14). The difference will be much
more remarkable, since the prediction error is greater.

Pertaining the computed task schedules (Figs. 12.15 and 12.16), since the prediction errors originating from both the irradiance and price forecast are also greater than the previous case, the difference between the optimal case and the sub optimal counterpart are much more evident. This result, also, suggests that the maximum and minimum errors, thus accounted with their sign, may be a set of indexes much more meaningful, towards the distortion of the task schedule, with respect to the MAE.

By simulating the task execution, based on each of the task schedule, the cumulative energy costs, depicted in Fig. 12.17 are obtained. The energy income amounts, on the other hand, are reported in Fig. 12.18, whereas the energy storage
level over time is presented in Fig. 12.19.

Although the involved values may differ from the previous case, the same conclusion still holds. For instance, the net energy cost of the optimal case amounts to 1.07$, the expected net cost of the sub optimal case amounts, on the other hand, to 11.718$, while the actual net cost of the sub optimal scheduling amounts to 1.73$.

If the baseline scenario is taken into account, it is possible to observe that the total energy cost amounts to 8.11$ and the total energy income amounts to 0.21$.

Since the net energy cost of the baseline scenario amounts to 7.9$, the net cost of the optimal case amounts to 13.5% of the baseline net energy cost. The net energy cost of the sub optimal case, on the other hand, equals the 21% of the baseline net cost.
Energy Demand Management Through Uncertain Data Forecasting: an Hybrid Approach

Based on the proposed evaluations, it appears that, while the prediction errors may affect the scheduling process, thus impairing the allocation of the tasks and the energy management, the performance loss is not directly related to the amount of said errors nor their interaction. Clearly, the forecast values used by the scheduler may promote or prevent the allocation of each time slot to the given tasks.

In this perspective, of course, the prediction errors may alter the time slots allocation in any way. However, if the optimal time slot for a given task can be addressed as the i-th time slot, and if a sub-optimal time slot assigned to the said task can be addressed as j-th time slot, it can be concluded that the performance loss actually depends on the difference between the i-th price and j-th price, that is the prices of the i-th time slot and the j-th time slot respectively.
Also, since the sub-optimal task allocation depends on both constraints and forecasts, due to the lack of correlation among the involved entities, it may be safe to assume that the sub-optimal allocation distortion is actually a random process, at least if a prediction error exists. On this subject, the “day 2” case, in which the prediction error is higher than 10% and lower than 20%, appears to be particularly meaningful.

In fact, if the optimal task schedule (Fig. 12.20) is compared against the sub optimal task schedule (Fig. 12.21), it is possible to notice that the “day 2” case is quite similar to the “day 3” one. However, in the “day 2” case, the net energy cost amounts to 32.218$ for the optimal and 32.235$ for the sub-optimal task schedule, thus there no meaningful difference in terms of energy cost between the optimal
and the sub-optimal case.

This aspect may also be seen as the reason why the scheduling process seems to be fairly robust against prediction error, in the sense that the entity of the performance loss does not seem directly bounded to the entity of the prediction error. Moreover, even if the performance loss is to be accounted, the improvement over a baseline scheme still remains remarkable.
12.7 Conclusion

The potential shown by task scheduling and energy management solutions within smart home environments, and the theoretical benefits for both users and providers, pointed out that in order to take advantage of such technology, a time ahead scheduling approach is mandatory. In order to investigate this hypothesis, a performance evaluation of a scheduling process based on a day ahead data forecast, is carried out.

The evaluation required, therefore, a few MLP based forecasters, that have been developed, implemented and trained. Then a forecast data set is generated. While the forecast data is used to select the time table under “realist conditions”, the historical data counterpart is used to simulate the task execution thus computing the resulting energy bill.

Also, the historical data are used to compute the ideal task scheduler, under the assumption that the prediction error is zero. Under these circumstances the optimal energy bill is computed and the comparison between the sub optimal and the optimal task scheduling processes take place.

By reiterating the same process over several data set, the relationship between prediction error and scheduling performance is analysed and evaluated, and then the conclusion are drawn. The investigation revealed that, while the issue at hand remains rather complex, a few key points can be highlighted.

Due to the interaction among prediction errors and constraints, the effects of prediction errors on the scheduling performance can hardly be esteemed. Even though indirectly, the historical data can be assumed to be responsible of the performance drop, whereas the performance drop does not appear to be bound to the entity of the prediction error.

While these results appear to be within reason, it also seems clear that, if more accurate forecasts are used, sub optimal task allocations are less likely to occur. Therefore, future works are aimed towards the improvement of data forecasts, to contain the prediction error, by providing additional information sources as the input of the ANN. Pertaining the irradiance and temperature forecasts, additional information on meteorological conditions can be used. Pertaining the price forecast also, grid load, fuel prices, and renewable source availability can be accounted.

In addition, although in the present work the point of view of the end user is taken into account, it shall be noted that the end user perspective is not the only one available. For instance, to investigate the power grid and the energy market behaviour in response to a large scale adoption of task schedulers may provide an interesting insight over power distribution.
References


Venayagamoorthy, G. (2011). Dynamic, stochastic, computational, and scalable technolo-

Frontiers of Intelligent Control and Information Processing