A Methodology for Energy Prediction and Optimization of a System based on the Energy Hub Concept using Particle Swarms

K. Kampouropoulos, F. Andrade
Fundació CTM Centre Tecnològic
Manresa, Spain

J. J. Cardenas, L. Romeral
MCIA Center, Electronic Dept.,
Technical University of Catalonia
Terrassa, Spain

Abstract—In this paper, a methodology for the energy prediction for the different consumptions of a system based in the Energy Hub concept is presented. The methodology that has been used for the energy prediction is based on an Adaptive Neuro-Fuzzy Inference System. An optimization method based on Particle Swarms has been used to minimize the energy cost of a system with multiple sources such as, photovoltaic, electrical grid and natural gas.

Keywords- Energy Prediction; Adaptive Neuro-Fuzzy Inference System; Energy Hub; Particle Swarm Optimization.

I. INTRODUCTION

With the continuously growing demand for energy, it is getting more important to develop new systems capable of managing the available energy with more efficient ways and minimize as much as possible the power losses in the electrical infrastructures. In addition to that, other issues such as the dependency on limited fossil energy resources, the restructuring of power industries and the general aim of utilizing more sustainable and environmentally friendly energy sources, raise the question whether piecewise changes of the existing systems are sufficient to cope with all these challenges or a more radical change in system design be needed.

Industrial, commercial, and residential consumers require various forms of energy services provided by different infrastructures. In the industrialized part of the world, coal, petroleum products, biomass, and grid-bound energy carriers such as electricity, natural gas, and district heating/cooling are typically used. So far, the different infrastructures are most often considered and operated independently. Combining the systems can result in a number of benefits [1].

The bibliography and the recent scientific paper publications show that the common mathematical approaches can resolve specific designed problems but are not sufficient to optimize an energy system that depends on multiple objectives. A multi-objective optimization problem involves conflicting objectives and has a set of Pareto optimal solutions. Techniques like Model Predictive Control (MPC), Optimal Control Dynamic Dispatch (OCDD), Dynamic Economic Dispatch (DED), Multi-Objective Evolutionary Algorithms (MOEA) and Genetic Algorithms (GA) are some methods that are being used to optimize the energy demand of a plant. The complexity of handling numerous objectives creates different advantages and disadvantages in the use of each method. A lot of these methods are deficient either in the efficiency of their results and solutions, or in the time that takes to process the data and find the solution [2].

II. STATE OF THE ART

A. Energy Hub Concept

An energy hub is considered as a unit where multiple energy carriers can be converted, conditioned and stored. It represents an interface between different energy infrastructures and/or loads. Energy hubs consume power at their input ports (connected to e.g. electricity and natural gas infrastructures) and provide certain required energy services (electricity, heating, cooling, compressed air, etc.) at the output ports. Within the hub, the energy is converted and conditioned using different power technologies (transformers, power electronic devices, compressors, heat exchangers and other equipment) [1]. From a system point of view, an energy hub can be identified as a unit that contains direct connections, energy converters and storage systems [3].

B. Energy Hub Benefits

Combining and coupling different energy carriers in energy hubs offers the following advantages:

-- The reliability of the supply of the energy can be increased from the load’s perspective because it is no longer fully dependent on a single network [4][5].

-- The hybrid ports of the hub offer an additional degree of freedom in supplying the loads. Considering for example the electrical load in Figure 1, it can be supplied by consuming electricity directly from the corresponding input or by generating part (or all) of the energy demand using the gas turbine or the energy storage. The hub can thereby substitute for an unattractive energy carrier (i.e., high tariff electricity). The load appears to be more flexible in terms of its price and...
its demand behavior, even if the actual load at the hub output remains constant.

The fact that various inputs and different combinations of them can be used to satisfy the energy demand allows the optimization of the system using different desired criteria (i.e., energy price, CO2 emissions, etc.).

The energy hub processes different energy carriers, each of which showing specific characteristics. Electricity, for example, can be transmitted over long distances with comparably low losses. Other forms of energy can be stored, offering the possibility to be used in a high demand period.

The energy hub optimization is to determine optimal transition strategies that bridge the gap between today’s portfolios and optimal future portfolios resulting from a Greenfield approach.

In [9], a topology with small scale generation technologies has been used considering heat and power portfolios. The optimization technique that has been implemented uses a dynamic programming method and it is based on a single-period mean-variance portfolio model. The system checks all the different possibilities of the system, calculating the energy generation costs of all the technologies in all scenarios. The objective of the application is to determine optimal transition strategies that bridge the gap between today’s portfolios and optimal future portfolios resulting from a Greenfield approach.

In [10], an implementation of a classic economic dispatch method has presented, using price relation between inputs and outputs to optimize the multi-energy structure. The objective is to minimize the general cost of the operation of the system. In this study, the costs for the demand of the energy carriers have been modeled as polynomials of the corresponding power. The cost of the energy carriers in this study have been considered as separated without any relation between them.

A study of an energy dispatch method which minimizes the cost of energy based on the energy hub concept and the carbon market rules was presented in [11]. Using a dispatch algorithm developed for a CCHP system provides the operational cost for users. Another optimization problem, where the objective is to minimize the integrated gas-electricity operation cost of the system has been studied in [12]. Case studies were presented integrating the IEEE-14 test system and the Belgian calorific gas network. The study uses an evolutionary strategy algorithm combined with Newton’s method and interior-point linear programming to solve the power flow problem and the gas natural balance.

### III. ENERGY HUB FORMULATION

For general investigations on the system level, steady state flow models are appropriate and commonly used. The flows through power converter devices can be analyzed by defining their energy efficiency as the ratio of steady state output and input. With multiple inputs and outputs, a conversion matrix can be defined which links the vectors of the corresponding power flows. Equation (1) outlines the modeling concept referred to the structure of Figure 2. The coupling matrix describes the transformation of power from the input to the output of the hub.

\[
\begin{bmatrix}
L_\alpha \\
L_\beta \\
L_\gamma \\
L_\delta
\end{bmatrix}
= 
\begin{bmatrix}
C_{\alpha\alpha} & C_{\alpha\beta} & \cdots & C_{\alpha\gamma} \\
C_{\beta\alpha} & C_{\beta\beta} & \cdots & C_{\beta\gamma} \\
\vdots & \vdots & \ddots & \vdots \\
C_{\gamma\alpha} & C_{\gamma\beta} & \cdots & C_{\gamma\gamma}
\end{bmatrix}
\begin{bmatrix}
P_\alpha \\
P_\beta \\
P_\gamma \\
P_\delta
\end{bmatrix}
\]

(1)

The models for the energy converters can be developed focusing on their input and output power flows, while
considering the device as a black box characterized by its
energy efficiency curve. There are four different types of
conversions that can be classified according to the number of
their inputs and outputs [3]:

- Single input and single output
- Single input and multiple outputs
- Multiple inputs and single output
- Multiple inputs and multiple outputs

The first part in (2) is related to antecedents and the second
part to consequents. The ANFIS structure executes these rules
and calculates the output through five layers (Fig. 4). The
layer 1 is called fuzzification. In the second layer, the weight
of each rule has to be computed by means of a fuzzy AND
operation. In the layer 3, it is made the normalization of the
values and in the layer 4 the defuzzification process. Finally in
layer 5, the overall output is obtained.

The particle swarm is similar to other evolutionary
computational methods, in the sense that a population (swarm)
comprised by individuals (particles) searches the space looking

A converter model can be developed in two steps. The
converter is considered firstly as a single input and single
output. Then the model is generalized for conversion with
multiple inputs and/or outputs. An example of an energy
converter block is presented in Figure 3 with its conversion
types (Table I).

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IV. ENERGY PREDICTION MODEL

ANFIS is an Adaptative network based on Takagi-Sugeno
fuzzy system. A fuzzy system is constructed of input and
output variables, membership functions, fuzzy rules and
inference method. In this case, the inputs are the energy
drivers, which are thought to affect the consumption profile
such as daily production, outdoor temperature, day of the week,
etc. The membership functions are the functions that define the
fuzzy sets [13].

The Figure 4 shows clearly the architecture of an ANFIS
structure with two inputs, four rules and one output. This
structure has a maximum of four rules and they are depicted in
the equation (2).

\[
\begin{align*}
\text{if } x \in A_1 \land B_1 & \Rightarrow z_1 = p_1 x + q_1 y + r_1 \\
\text{if } x \in A_1 \land B_2 & \Rightarrow z_2 = p_2 x + q_2 y + r_2 \\
\text{if } x \in A_2 \land B_1 & \Rightarrow z_3 = p_3 x + q_3 y + r_3 \\
\text{if } x \in A_2 \land B_2 & \Rightarrow z_4 = p_4 x + q_4 y + r_4 
\end{align*}
\]

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values and in the layer 4 the defuzzification process. Finally in
layer 5, the overall output is obtained.

V. PARTICLE SWARM OPTIMIZATION

Proposed by Kennedy and Eberhart (1995), this method
consists in a fitness optimization through the exchange of
information between elements (particles) of the group,
resulting in a strong, efficient and non-deterministic
optimization algorithm of easy computer implementation [14].
for an appropriate solution of a given problem. However, in particle swarm optimization, each individual has a speed which is responsible for space exploration (evolution) and a memory to store the best position already visited. Besides, the algorithm also takes into account the best position found by the population.

The next displacement of a particle is being calculated depending of its own velocity, its best performance and the best performance of its best informant [15]. The particle movement can be seen in Fig. 5.

VI. PRACTICAL APPLICATION

For the analysis of the prediction method based on ANFIS and the optimization of the system by the use of Particle Swarm Optimization, a multi-energy system has designed, based in the energy hub concept. The next figure represents the schematic block of the system.

The system contains as supply sources: a photovoltaic park (with total power of 60 kWp), the electrical grid and natural gas. Including different energetic infrastructures such as a heat pump and a cogeneration system, it is able to convert the electrical power to heat and the natural gas to electricity. The energy profile of the photovoltaic installation can be seen in Fig. 7.

The mathematical models of two electrical and two thermal consumptions have been calculated, training the ANFIS structure using a data base with historic energy demand. Different operation parameters have been considered in the data base, such as: energy demand, climatic data and day time. A comparison between the energy demand and the energy prediction, calculated by the ANFIS structure can be seen in Fig. 8 to Fig. 11.
The different converter outputs (nodes) of the system can be expressed as the product of input and efficiency:

\[ P_1 = P_{pv} \eta_{ir} \]  \hspace{1cm} (3a)
\[ P_2 = P_{grid} \]  \hspace{1cm} (3b)
\[ P_3 = P_{grid} v_2 + P_{pv} v_1 \]  \hspace{1cm} (3c)
\[ P_4 = P_{grid} (1 - v_2) + P_{pv} (1 - v_1) \]  \hspace{1cm} (3d)
\[ P_5 = P_{pump} \eta_{pump} \]  \hspace{1cm} (3e)
\[ P_6 = P_{gas} \eta_{el} \]  \hspace{1cm} (3f)
\[ P_7 = P_{gas} \eta_{heat} \]  \hspace{1cm} (3g)
\[ P_8 = P_3 + P_6 \]  \hspace{1cm} (3h)
\[ P_9 = P_7 + P_5 \]  \hspace{1cm} (3i)

The final power yields can be formulated as:

\[ P_{el}^{out} = P_{grid} v_2 + P_{gas} \eta_{el} + P_{pv} \eta_{ir} v_1 \]  \hspace{1cm} (4a)
\[ P_{heat}^{out} = P_{grid} \eta_p (1 - v_2) + P_{gas} \eta_{heat} + P_{pv} \eta_{ir} \eta_p (1 - v_1) \]  \hspace{1cm} (4b)

The variables \( v_1 \) and \( v_2 \) indicate the percentage of the power of the electrical grid and photovoltaic system that is being used to supply the electrical consumptions. The rest of the energy is being converted to thermal energy by the heat pump. The variables \( \eta_{el}^{CHP} \) and \( \eta_{heat}^{CHP} \) indicate the conversion values of the cogeneration system for generation of heating and electricity. The variable \( \eta_{ir} \) indicates the efficiency of the transformation block and the \( \eta_{pump} \) indicates the conversion value to transform the electricity to heat via the heat pump.

The conversion from the input to the output of the hub can be described with an input-output coupling matrix:

\[
\begin{bmatrix}
P_{el}^{out} \\
P_{heat}^{out}
\end{bmatrix}
= 
\begin{bmatrix}
v_2 & \eta_{ir} v_1 & \eta_{el} \\
\eta_{pump} (1 - v_2) & \eta_{pump} \eta_{ir} (1 - v_1) & \eta_{heat}
\end{bmatrix}
\begin{bmatrix}
P_{grid}^{in} \\
P_{pv}^{in} \\
P_{gas}^{in}
\end{bmatrix}
\]  \hspace{1cm} (5)

The cost matrix of the different energy supplies can be defined as:

\[ C_{total} = C_{grid} + C_{gas} + C_{pv} \]  \hspace{1cm} (6)

Finally the optimization problem can be stated as:

\[ \minimize \quad C_{total} \]  \hspace{1cm} (7)
\[ \subjectto \quad P_{in}^{out} = CP_{in}^{total} \]
\[ P_{min} \leq P_{in}^{in} \leq P_{max} \]

The optimization results are presented in Fig. 12. The algorithm controls the amount of energy that each source supplies, minimizing the total cost.

VII. CONCLUSIONS

In this paper, a methodology for the energy prediction of different consumptions is presented, using an Adaptive Neuro-Fuzzy Inference System. For the training of the algorithm, a data base is used with historic data of the consumptions, in relation to external parameters such as: calendar information and climatic data. The proposed methodology for the energy prediction enables the user to short and long forecasting for different types of consumptions using external parameters that can affect in their operation.

A multi-source and multi-product system that contains photovoltaic energy, electrical grid connection and natural gas supply, is formulated in terms of the Energy Hub concept. An optimization algorithm based on Particle Swarms is implemented with objective to obtain the most economic operation of the energy use, satisfying the energy forecasted demand of the consumptions of the system. The formulation of the Energy Hub, clarify the mechanisms taking place in a systems with multiple energy carriers. The implementation of the optimization algorithm can be formulated in a different way, changing the optimization parameters.

Also is noted, for future works, that the optimization algorithm can be improved, using multi-objective criteria. Also the implementation of an energy storage system could change the operation strategy offering different advantages to the system.
Figure 12. Optimization results of the Energy Hub system using a Particle Swarm Optimization.