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 additional 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.

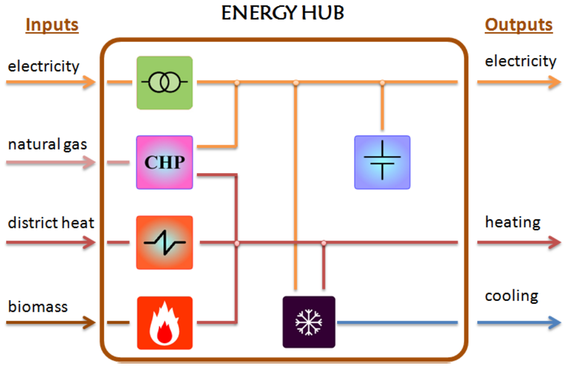

Figure 1. Example of an energy hub structure.

C. *Energy Hub Optimization*

In the past, different methods of optimization have been developed on systems with only one form of energy such as electricity, natural gas and district heating networks. More recently, the combined modeling and analysis of energy systems with multiple energy sources have been studied in a number of publications. Different approaches have been implemented with objective to model a multi-energy system and to optimize its operation. The most of the optimization researches that have been used have as objective to optimize a specific unit (either economical or environmental) in the pilot system, using different type of mathematical models to formulate the system's structure (polynomial models, statistic models, etc.).

Originally, the energy hub approach was developed for Greenfield design studies but in the meantime the concept has been taken over for other purposes. Application of the energy hub concept for the characterization of trigeneration devices is reported in [4] and [5]. The trigeneration system is proposed for the simultaneous production of chemicals, power and heat, being characterized as a multi-source multi-product system. Another application example is the conception of fuel cell systems and models for the integrated analysis of energy and transportation systems [6]. An application of mean-variance portfolio theory to a model of multiple forms of energy such as electricity, heating and cooling power, has been studied in [7]. The scenario is obtained using a cost matrix for the electricity, the heat output and the cooling. Another study of power flow and optimization approach for power systems including multiple energy carriers, such as electricity, natural gas and district heat is presented in [8]. The optimization approach uses the optimal demand, the conversion and the transmission of multiple energy carriers within a system and formulated as a combined optimal power flow problem. Although the presented mathematical model can optimize the functionality of the system, it is not sufficiently accurate for other optimal power flow applications.

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.

$$\begin{bmatrix} L_\alpha \\ L_\beta \\ \vdots \\ L_\omega \end{bmatrix} = \begin{bmatrix} C_{\alpha\alpha} & C_{\beta\alpha} & \cdots & C_{\omega\alpha} \\ C_{\alpha\beta} & C_{\beta\beta} & \cdots & C_{\omega\beta} \\ \vdots & \cdots & \ddots & \vdots \\ C_{\alpha\omega} & C_{\beta\omega} & \cdots & C_{\omega\omega} \end{bmatrix} * \begin{bmatrix} P_\alpha \\ P_\beta \\ \vdots \\ P_\omega \end{bmatrix} \qquad (1)$$

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

Figure 2. Energy carriers of an energy hub.

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 1).

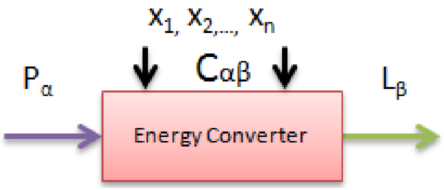

Figure 3. Energy converter example with single input and single output.

TABLE I. CONVERSION TYPES

Type of Coupling	*Coupling Factor*	*Energy Carriers*
zLossless transmission	$C\alpha\beta = 1$	$\alpha = \beta$
Lossy transmission	$0 < C\alpha\beta \leq 1$	$\alpha = \beta$
Lossless conversion	$C\alpha\beta = 1$	$\alpha \neq \beta$
Lossy conversion	$0 < C\alpha\beta \leq 1$	$\alpha \neq \beta$
No coupling	$C\alpha\beta = 0$	Any α,β

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).

$$\begin{aligned} &if \;\; x \in A_1 \wedge B_1 \Rightarrow z_1 = p_1 x + q_1 y + r_1 \\ &if \;\; x \in A_1 \wedge B_2 \Rightarrow z_2 = p_2 x + q_2 y + r_2 \\ &if \;\; x \in A_2 \wedge B_1 \Rightarrow z_3 = p_3 x + q_3 y + r_3 \\ &if \;\; x \in A_2 \wedge B_2 \Rightarrow z_4 = p_4 x + q_4 y + r_4 \end{aligned} \tag{2}$$

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.

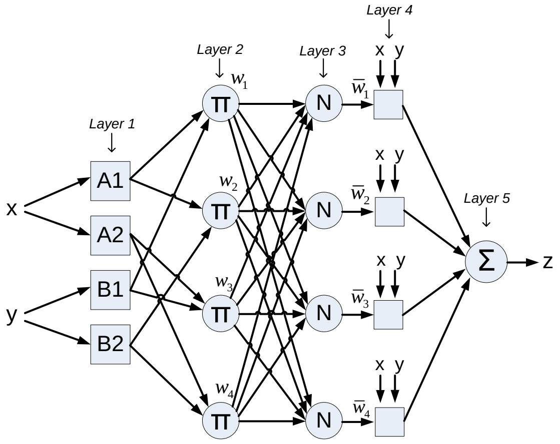

Figure 4. ANFIS architecture: two inputs, four if-then rules and one output.

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].

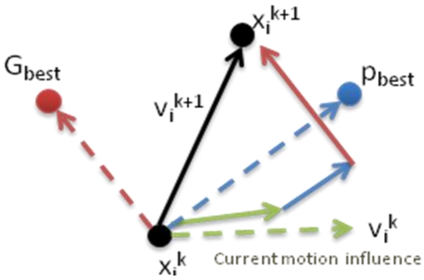

Figure 5. Velocity and position updated in the particles of PSO.

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 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.

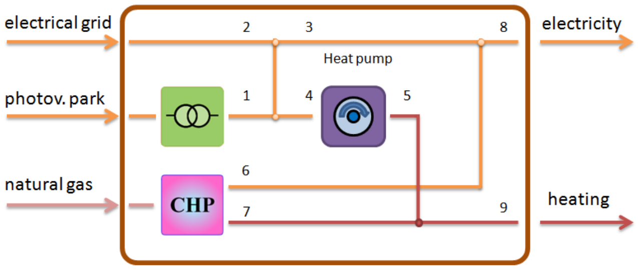

Figure 6. Block diagram of the energy hub system, indicating the different system nodes

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.

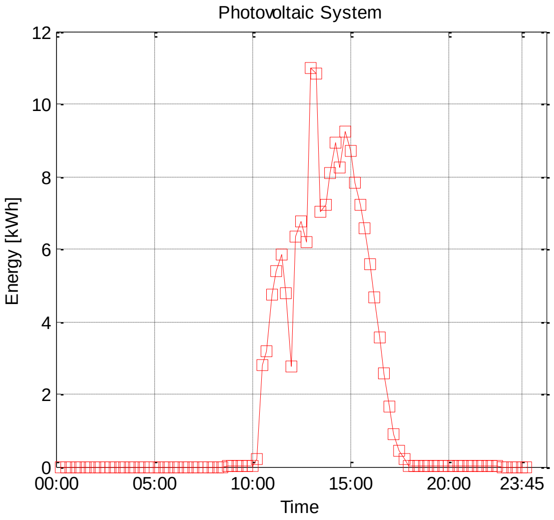

Figure 7. Energy profile of the photovoltaic system during a day.

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.

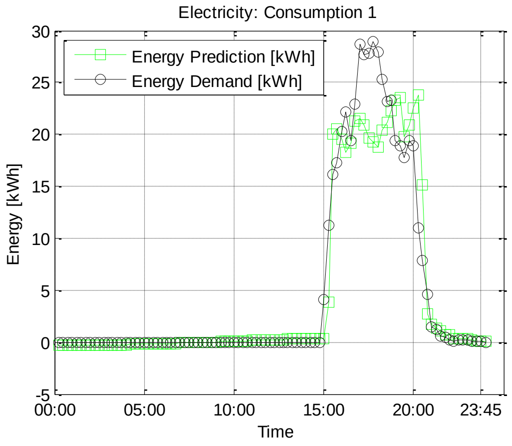

Figure 8. Energy prediction of an electric consumption using ANFIS.

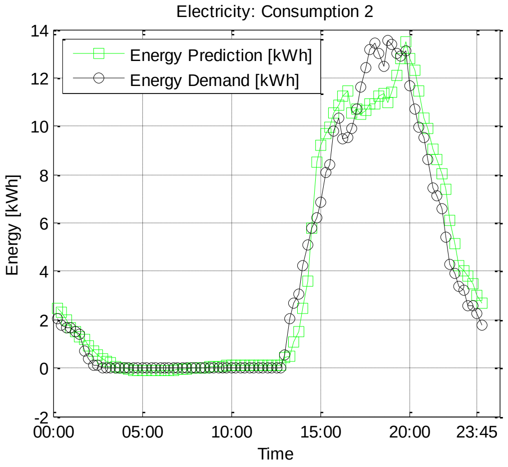

Figure 9. Energy prediction of an electric consumption using the ANFIS.

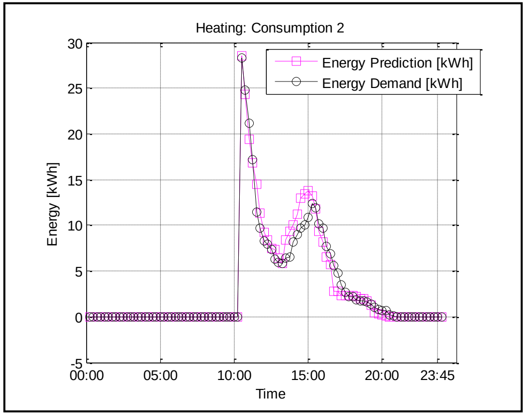

Figure 10. Energy prediction of a thermal consumption using ANFIS.

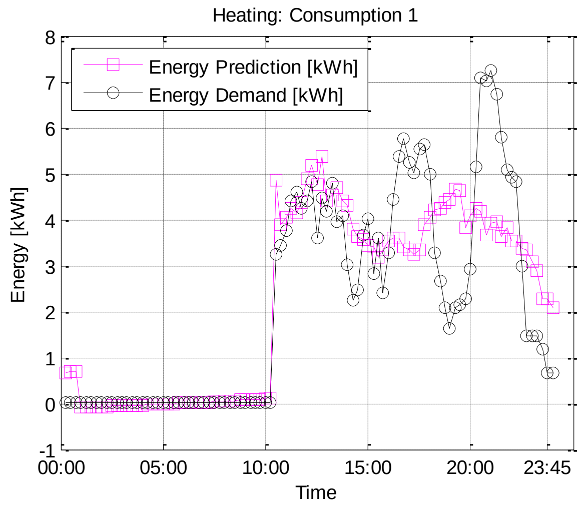

Figure 11. Energy prediction of a thermal consumption using ANFIS.

The different converter outputs (nodes) of the system can be expressed as the product of input and efficiency:

$$P_1 = P_{pv}\eta_{\mathrm{tr}} \tag{3a}$$

$$P_2 = P_{grid} \tag{3b}$$

$$P_3 = P_{grid}v_2 + P_1v_1 \tag{3c}$$

$$P_4 = P_{grid}(1-v_2) + P_1(1-v_1) \tag{3d}$$

$$P_5 = P_4\eta_{\mathrm{pump}} \tag{3e}$$

$$P_6 = P_{gas}\eta_{\mathrm{el}}^{\mathrm{CHP}} \tag{3f}$$

$$P_7 = P_{gas}\eta_{\mathrm{heat}}^{\mathrm{CHP}} \tag{3g}$$

$$P_8 = P_3 + P_6 \tag{3h}$$

$$P_9 = P_7 + P_5 \tag{3i}$$

The final power yields can be formulated as:

$$P_{el}^{out} = P_{grid}v_2 + P_{gas}\eta_{\mathrm{el}}^{\mathrm{CHP}} + P_{pv}\eta_{\mathrm{tr}}v_1 \tag{4a}$$

$$P_{heat}^{out} = P_{grid}\eta_{\mathrm{p}}(1-v_2) + P_{gas}\eta_{\mathrm{heat}}^{\mathrm{CHP}} + P_{pv}\eta_{\mathrm{tr}}\eta_{\mathrm{p}}(1-v_1) \tag{4b}$$

The variables v1 and v2 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 $\eta_{\mathrm{heat}}^{\mathrm{CHP}}$ and $\eta_{\mathrm{el}}^{\mathrm{CHP}}$ indicate the conversion values of the cogeneration system for generation of heating and electricity. The variable η_{tr} indicates the efficiency of the transformation block and the η_{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:

$$\begin{bmatrix} P_{el}^{out} \\ P_{\mathrm{heat}}^{out} \end{bmatrix} = \begin{bmatrix} v_2 & \eta_{\mathrm{tr}}v_1 & \eta_{\mathrm{el}}^{\mathrm{CHP}} \\ \eta_{\mathrm{pump}}(1-v_2) & \eta_{\mathrm{pump}}\eta_{\mathrm{tr}}(1-v_1) & \eta_{\mathrm{heat}}^{\mathrm{CHP}} \end{bmatrix} * \begin{bmatrix} P_{grid}^{in} \\ P_{pv}^{in} \\ P_{gas}^{in} \end{bmatrix} \tag{5}$$

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

$$C_{total} = C_{grid} + C_{gas} + C_{pv} \tag{6}$$

Finally the optimization problem can be stated as:

$$\begin{aligned} \min imize: \quad & C_{total} \\ subject\ to: \quad & P_{total}^{out} = CP_{total}^{in} \\ & \overline{P}_{\min}^{in} \leq \overline{P}^{in} \leq \overline{P}_{\max}^{in} \end{aligned} \tag{7}$$

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.

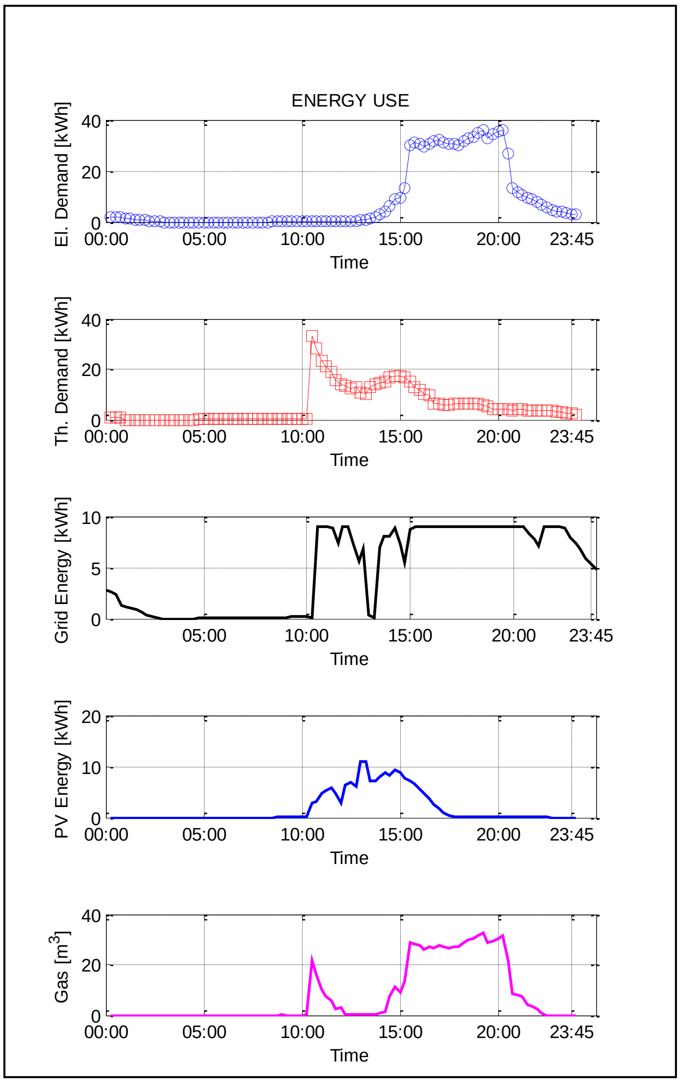

Figure 12. Optimization results of the Energy Hub system using a Particle Swarm Optimization.

VIII. REFERENCES

[1] M. Geidl, G. Koeppel, P. Favre-Perrod, B. Klockl, G. Andersson, K. Frohlich, “The energy hub – A power concept for future energy systems,” Third Annual Carnegie Mellon Conference on the Electricity Industry, Mar 2007.

[2] Aimin Zhou, Bo-Yang Qu, Hui Li, Shi-Zheng Zhao, Ponnuthurai Nagarathnam Suganthan, Qingfu Zhang, “Multiobjective evolutionary algorithms: A survey of the state of the art,” Swarm and Evolutionary Computation, Volume 1, Issue 1, 2011, Pages 32-49.

[3] M. Geidl, “Integrated modeling and optimization of multi-carrier energy systems,” University of Zurich, Thesis Project, 2007.

[4] G. Chicco and P. Mancarella, “A comprehensive approach to the characterization of trigeneration systems,” In Proc. of 6th World Energy System Conference, Turin, Italy, 2006.

[5] K. Hemmes, J. L. Zachariah-Wolff, M. Geidl, and G. Andersson, “Towards multi-source multi-product energy systems,” International Journal of Hydrogen Energy.

[6] B. Marti,“ Integrated analysis of energy and transportation systems,” Master thesis, Power Systems Laboratory, ETH Zurich, 2006.

[7] Kiezle, G. Andersson, “Efficient multi-energy generation portfolios for the future,” 4th Annual Carnegie Mellon Conference on the Electricity Industry, 2008.

[8] M. Geidl, G. Andersson, “A modeling and optimization approach for multiple energy carrier power flow,” IEEE PES PowerTech, St. Petersburg, Russian Federation, 2005.

[9] F. Kiezle, G. Andersson, “A greenfield approach to the future supply of multiple energy carriers,” 2009 IEEE Power Energy Society General Meeting (2009).

[10] M. Geidl, G. Andersson, “Optimal power dispatch and conversion in systems with multiple energy carriers, 2005.

[11] A.Sheikhi, A.M.Ranjbar, F.Safe, “Optimal dispatch of a multiple energy carrier system equipped with a CCHP,” Department of Electrical Engineering, Sharif University of Technology, Tehran, Iran, 2011.

[12] C. Unsihuay, J. W. M. Lima, A. C. Z. de Souza, and Ieee, “Modeling the integrated natural gas and electricity optimal power flow,” 2007 Ieee Power Engineering Society General Meeting, Vols 1-10, pp. 3955-3961, 2007.

[13] J. J. Cardenas, A. Garcia, J. L. Romeral, and K. Kampouropoulos, “Evolutive ANFIS training for energy load profile forecast for an IEMS in an Automated Factory,” in ETFA2011, the IEEE 2011 Conference on Emerging Technologies and Factory Automation, Toulouse, France, 2011.

[14] C. A. Souza Lima, Jr., C. M. F. Lapa, C. M. d. N. A. Pereira, J. J. da Cunha, and A. C. M. Alvim, “Comparison of computational performance of GA and PSO optimization techniques when designing similar systems - Typical PWR core case,” Annals of Nuclear Energy, vol. 38, pp. 1339-1346, Jun 2011.

[15] M. Clerc, “Particle swarm optimization,” ISBN-13: 978-1-905209-04-0, 2006.