



HAL
open science

Testing and Evaluation of Dynamic Energy Simulations for the development of an Intelligent Management of Energy for the ADREAM Smart Building

Ilias Papas, Bruno Estibals, Christelle Ecrepont, Corinne Alonso

► **To cite this version:**

Ilias Papas, Bruno Estibals, Christelle Ecrepont, Corinne Alonso. Testing and Evaluation of Dynamic Energy Simulations for the development of an Intelligent Management of Energy for the ADREAM Smart Building. Smart World Congress 2017, Aug 2017, San Francisco, United States. 7p. hal-01699215

HAL Id: hal-01699215

<https://laas.hal.science/hal-01699215>

Submitted on 2 Feb 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Testing and Evaluation of Dynamic Energy Simulations for the development of an Intelligent Management of Energy for the ADREAM Smart Building

Ilias PAPAS, Bruno ESTIBALS, Christelle ECREPONT, Corinne ALONSO
LAAS-CNRS
7, Avenue du colonel Roche
31077 Toulouse Cedex 4, France
E-mail : ipapas@laas.fr

Abstract - Having 6500 integrated sensors and a wide network of embedded systems, ADREAM can be categorized as one of the prototype smart buildings of France. As needs for intelligent management of energy on a city scale are growing, the ADREAM project provides a multidisciplinary platform of experimentation, developing solutions for efficient Energy Networks and Smart Grids. This paper provides the description of the project along with an overview of the various energy and control systems installed. Three different modeling techniques are presented, illustrating their strengths and limitations on simulating the thermal behavior of the building and the functioning of the different energy systems. A thermal model of the building was developed and calibrated for thermal analysis and energy consumption prediction, using the software Pleiades+Comfie. A “black box” model was developed for the simulation of energy system parameters and the exploration of efficient control strategies. A modeling technique using Dynamic Neural Networks was also developed for a more precise modeling of the various systems and their outputs. The conclusion addresses the utility of exploring and combining different types of models for optimizing the energy management of Smart Buildings.

Keywords - Smart Building, Building Simulation, Energy Optimization, Pleiades + Comfie, Simulation methodology, Model Calibration, Simulink, Dynamic Neural Networks

I. INTRODUCTION

Energy management and optimization is a growing issue for our society. As buildings account for about 40% of the global energy consumption, the EU proposes a target of 27% more energy savings by 2030 [1]. The global initiative for energy optimization gave rise to the concept of Zero Energy Buildings (ZEB), which was first defined in scientific literature in 2006, but it had not been translated concretely into laws and norms. After the National Renewable Energy Laboratory (NREL) proposed an initial definition, Aalborg University produced a state of the art synthesis of ZEB definitions [2] [3]. Thus, the research focused on demonstrations over one-year-cycles, which eventually highlighted the fact that energy demand for heating and electrical consumption needs to be minimized. At the same time, the energy supply should rely completely on a building's

annual production of renewable energy [4] [5]. The most common source exploited for energy production is solar energy. The development of buildings that aim to minimize consumption while maximizing production of energy promoted the spread of Building Integrated Photovoltaic (BIPV) systems.

However, for confronting any associated problems, a building must rely on the conception of New Generation Energy Networks, which need to be reactive and adaptive. Advanced Energy Networks must possess validated performance and functioning properties in terms of production, consumption and command. They need to accept multiple heterogeneous sources in terms of technology, availability and power, responding adequately and accurately to rapid, non-anticipated, variations by the user. It is these needs that gave rise to the concept of a Smart Grid, an energy network that not only deals with energy transportation, but also with telecommunication, measurement (sensors) and advanced management. According to Isa [6], a smart grid should have the ability to improve safety and efficiency, make better use of existing assets, enhance the reliability and power quality, reduce dependence on imported energy, and minimize costly environmental impact. As Mohammed et al indicate [7], it is essential to integrate renewable sources into a smart grid for the reduction of financial and environmental costs, as numerous energy models have been studied for the prediction and optimization of power production through solar panels, geothermal energy, and wind turbines.

Examples of sustainable and smart buildings are the Solaris project in the Paris region [8], and the Edge in Amsterdam [9]. Both buildings share the same objectives in terms of intelligent and optimized energy management, but they are both conceived, built and managed in different ways. The Solaris project involves the efficient use of geothermal and solar energy for covering the needs of a 25000 m² surface, designed and built with materials and techniques according to France's low energy consumption building standard [8]. On the other hand, the Edge project revolves around a completely different strategy for achieving sustainability, where, besides the efficient natural ventilation

system and the electricity produced by solar panels, users have the capacity to interact through a central dashboard with a large number of elements in the building. This strategy allows better use of energy according to occupation levels, more efficient use of electrical machines, and a more optimized comfort through individual adjustments of temperature and lighting.

These buildings consist of only two examples among the hundreds that exist and focus on smart energy management on a building's scale. Thus, the ADREAM project, combining ideas from both designs, aims to stand as one of the world's prototype models for intelligent energy management. This paper presents the ADREAM project in Section II. The description and analysis of the various modeling strategies that aim to predict electrical consumption is given in Sections III, IV, and V. Section VI provides the evaluation of the associated results and concludes on the ongoing research, while it outlines the future work.

II. THE ADREAM PROJECT

A. Objectives

The ADREAM project (French acronym for *Embedded Reconfigurable Dynamic Autonomous and Mobile Architectures*) is a research program focused on Smart Grids, micro-grids, BIPV systems, as well as on Ambient Physical Cyber Systems [10]. Figure 1 shows an aerial view of the building along with its large PV surface.



Fig. 1. Aerial view of the ADREAM building

The scientific objectives associated with ADREAM are based on all aspects linked to the concept and evaluation of New Generation Energy Networks. The related domains include power electronics, data processing, security functioning, and automation.

This paper focuses on ADREAM's objective of developing a modeling approach to energy management and optimization for the totality of the systems, integrating all the entities of production and consumption, by deploying the extensive network of intelligent sensors and regulators. The presented work provides an overview of three different modeling and simulation methods whose aim is to explore applicable solutions for the energy consumption optimization objective of ADREAM through an intelligent management of energy.

The first method involves the calibration of a Dynamic Thermal Simulation for the purpose of analyzing the thermal

behavior of the building and reducing its electrical consumption. The second method describes the "black box" modeling method with the objective of exploring optimized control strategies. The third part presents a modeling approach which exploits the capacities of Dynamic Neural Networks. The last part of this project introduces the initial development phase of an inclusive Simulink model which represents the totality of the ADREAM energy network. This method aims to provide an optimal configuration of the systems' parameters, which can serve as a prototype example for a sustainable building.

B. Energy Systems

This study focuses on the transfer of energy within the ADREAM building taking into account the heating, the air conditioning, the lighting, and the various electronic devices. ADREAM is connected to an electrical grid which benefits from a total of 100kWc of photovoltaic energy. In addition, it involves the use of geothermal energy through the installation of three ground source heat pumps (135kW). The hygienic ventilation system is also linked to a ground heat exchanger to minimize the heating/cooling energy needs of the air. The notion of the Smart Grid is examined extensively through the ADREAM research program as the electrical energy surplus from the photovoltaic production, combined with the optimized consumption of high performance HVAC (Heating, Ventilation, and Air Conditioning) systems, can be transported to the rest of the buildings composing the LAAS-CNRS laboratory. The principal objective of the ADREAM project was to give rise to a building of optimized energy consumption and production, while achieving periodical states of positive energy, without compromising user comfort. Figure 2 illustrates the various energy systems installed in the building.

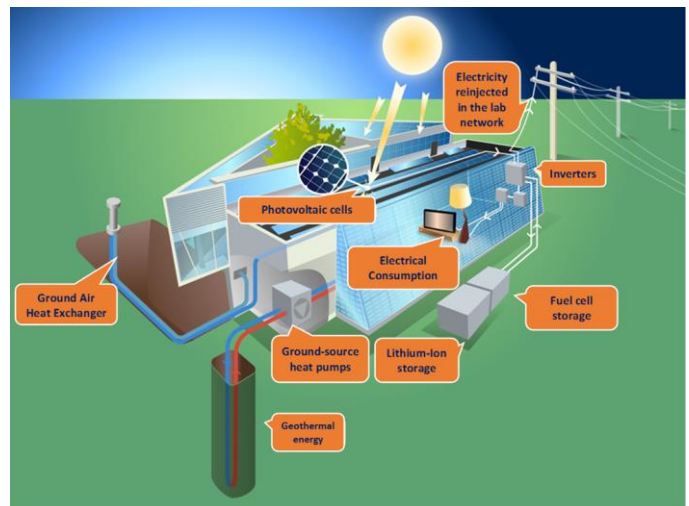


Fig. 2. Energy systems installed in ADREAM

C. Supervision System and Database

ADREAM is an instrumented building which is connected to a control and supervision system. Coupled with a database, the system allows the registration of measurements for reporting and analysis purposes. The control and supervision is carried out through the software PCVue, developed by *ARC Informatique* [11], adapted to the technical specifications of the building. This system is tied to 6500 integrated sensors and various controllers (WAGO, TAC) which regulate the whole

installation. The registration of the data takes place periodically with a frequency varying from 1 to 5 minutes, according to the different setup of each sensor. This information is then measured, posted, and registered by the PCVue software. The daily number of data points registered in the database can reach 500000. The objective of this management system is, on one hand to assure the automatic functioning of the building (thermal and lighting regulation with the possibility of minor variations by the occupants according to their comfort perception), and on the other hand to supervise in real time the operation of the diverse interconnected equipment for the purpose of a detailed energetic analysis and optimization. The PCVue program allows the surveillance of the intelligent lighting system, the functioning and control of the HVAC systems, and the supervision of the photovoltaic production along with the electrical consumption.

III. DYNAMIC THERMAL SIMULATION

A. Principles and Software

A Dynamic Thermal Simulation (DTS) serves as a computer tool that allows the thermal study and energetic assessment of a building from multiple perspectives (temperature profiles, energy consumption, comfort). The interest for this type of modeling stems from the motivation to simulate with high precision the particular architecture of ADREAM's structure, along with its thermal properties and the technical characteristics of the systems installed. The challenge of this task lied in the complex nature and interaction of the various HVAC systems, as well as in the polyvalent usage of the building (volatile occupation and utilization of electronic equipment). Once the initial phase of the thermal modeling was completed, the calibration process of the resulting model was accomplished through the extensive exploitation of the data registered by the numerous integrated sensors. As suggested by the definition of a DTS, this project aims to analyze the existing conditions of the building in terms of its thermal behavior and energy consumption, as well as to predict the corresponding results of a parametric variation study. The purpose of a parametric variation, according to possible realistic installation and regulation upgrades, is to identify the potential problems related to the existing configuration and to provide the framework of an improvement strategy. That is, by simulating multiple scenarios of solutions, the main objective of this study is the optimization of energy consumption and management through ameliorations of the existing installation and on the regulation of the HVAC systems functioning.

The initial modeling phase of the building ADREAM was carried out by the software Pleiades + Comfie (P+C) [12]. P+C is a widely used thermal simulation program developed at the Ecole des Mines in Paris and supplied by the company Izuba. As indicated by Peuportier [13], P+C can be considered as a precise simulation tool for the generation of temperature evolution and energetic needs profiles, as well as for the study of their sensibility to main thermal parameters. The choice of the software for the purpose of this project was based on: a) the consistent development of the software through frequent updates which involve additional parametrization options, b) experience of use, and c) a "user-friendly" interface. The main entry parameters involved in the modeling process of ADREAM with the P+C program employed the thermal characteristics of its structure, the scenarios of usage, the systems characteristics and a complete weather file. This file

was based on the data extracted by the meteorological station installed on the roof of the building. The key parameters, for which an extensive analysis was needed in order to be estimated as precisely as possible, consisted of: a) the presence of a very wide range of electronic devices for the purpose of a diverse research program expanding from robotics to energy production optimization, b) the significant variation of the occupation levels from a weekly and yearly point of view, and c) the uncertainty of the users' actions on the regulation of their offices (temperature and ventilation set points). Even though P+C does not have a Model Predictive Control (MPC) capacity, it allows the possibility of further model refinement on a weekly and yearly basis for certain scenarios which depend on highly variable parameters (temperature set points, ventilation air flow, solar protection, internal heat gains based on electronic device usage and occupation). Figure 3 depicts the 3D model of the building as designed with P+C. Once the input of the fixed parameters was completed and the first simulations were launched, the variable parameters were exploited for the purpose of a reasonable and accurate calibration process. The calibration phase was mainly based on the identification of errors in the model that depended highly on the variable parameters mentioned above. Thus, their extensive analysis was performed with the help of the data registered by the various integrated sensors in accordance with multiple hypotheses. The specificities of the model algorithm, the detailed modeling process, and the hypotheses involved, are elaborated extensively on a previous paper by Papas et al [14].

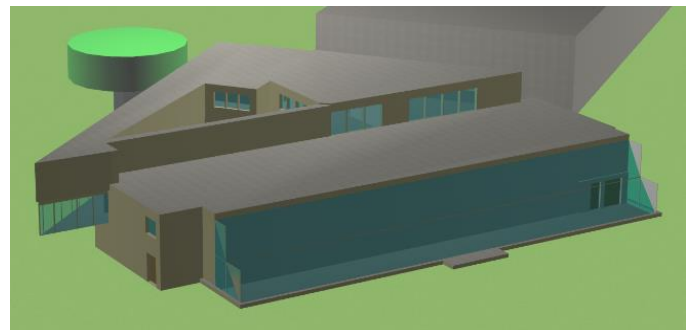


Fig. 3. 3D model of ADREAM in the Pleiades+Comfie interface

B. Calibration and Results

After the entry of all the parameters in the P+C software and the run of the first simulations, it was important to compare the results with real data as registered by the integrated sensors. This comparison served as a model calibration process. Prior to this phase, an extensive analysis and treatment of the registered data was carried out. Data collection and analysis was facilitated with the use of MatLab, through which it was possible to adjust: a) the format, and b) the time-step of temperature measurements to 1-hour intervals, matching the time-step of the P+C simulation results. Once the temperature data for all the zones was produced in the right format, it was possible to compare it with the results of the simulation on a short-term (2-3 weeks) and long-term (full year) basis.

The calibration process was completed through the calculation of two statistical indicators, as proposed by the ASHRAE Guideline 14-2002 [15]. Model calibration between simulated and measured data can be estimated with the use of the Normalized Mean Bias Error (NMBE) and the Coefficient of Variation of Root Square Mean Error CV(RMSE). These

indicators are written in the form of the equations 1 and 2 respectively.

$$NMBE (\%) = \frac{\sum_{i=1}^n (T_{sim} - T_{mes})}{n - 1} \cdot \frac{1}{\overline{T_{mes}}} \cdot 100 \quad (1)$$

Where:

T_{sim}: Simulated temperature value

T_{mes}: Measured temperature value

$\overline{T_{mes}}$: Arithmetic mean of the sample of n measurements

n: number of data points (temperature values)

As described by Nguyen [16], a positive value of NMBE indicates an over-estimate while a negative value shows an under-estimate by the model. An ideal NMBE should be around 0.

$$CV(RMSE)(\%) = \sqrt{\frac{\sum_{i=1}^n (T_{sim} - T_{mes})^2}{n - 1}} \cdot \frac{1}{\overline{T_{mes}}} \cdot 100 \quad (2)$$

Estimating model fitting with the use of CV(RMSE) demonstrates the differences in values between measured and simulated data. CV(RMSE) is always positive and an ideal value is close to 0.

For our study, a NMBE lower than 1% and a CV(RMSE) less than 10% were considered as accurate indicators of a precise thermal model for the purpose of a parametric variation that aims to optimize energy management.

The P+C model was calibrated after a series of validated estimations and hypotheses, which were based on *in situ* measurements and information extracted from a survey on the ADREAM's occupants. Table 1 shows the evolution of the statistical indicators (NMBE and CV(RMSE)) from the initial to the final simulation, while Figure 4 illustrates the fit between measured data (T_REAL) and simulated data (T_INITIAL_SIMULATION and T_FINAL_SIMULATION) for the evolution of the interior temperature of an office.

Table 1: Statistical indicators for the initial and final simulations

Statistical Indicator	T_INITIAL SIMULATION	T_FINAL SIMULATION
NMBE	4.57%	0.48%
CV(RMSE)	5.51%	2.84%

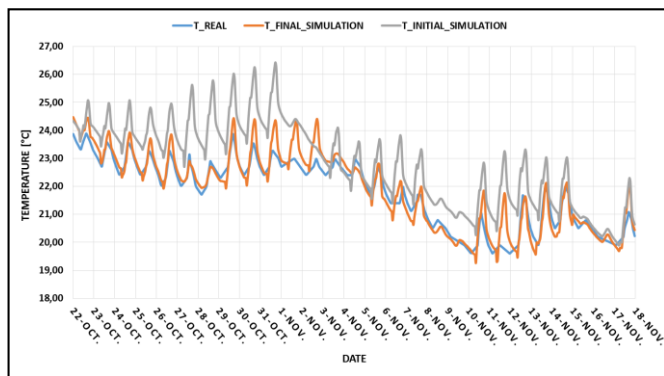


Fig. 4. Example of the model calibration of an office for a 2-month period

The final step for carrying out a complete simulation including the building's thermal behavior analysis, as well as its electrical consumptions, involved the entry of all the HVAC systems' parameters. That is, in order to launch a complete simulation the required information concerned all the technical parameters of: a) the three heat pumps, b) the central AHU and the five individual AHU's, c) the ceiling fan coils, and d) the radiators. The technical parameters concern variables such as: the coefficient of performance, the power consumed by the ventilators, the length of the circuit, the functioning temperature set-point, etc. Once the corresponding parameters were entered in the P+C interface and connected appropriately to the rest of the project, the complete simulation was initiated. The calibration process was repeated for the complete simulation in a similar way as for the base DTS. The most important adjustment concerned the heat pumps' coefficient of performance (COP), which was increased according to the real data values registered in the system and was slightly superior to the COP provided by the supplier. In addition, the theoretical air flow values given by the supplier of the AHU were corrected according to the measured values. Thus, the final results concerning the electrical consumption per source were compared to the measured values supplied by the laboratory and are presented in Table 2.

Table 2: Comparison between real and simulated electrical consumption by source

Consumption Source	Real Consumptions [MWh/an]	Simulated Consumption s [MWh/an]	Relative Error [%]
Heat Pump 1	9,03	35,41	3,05
Heat Pump 2	16,71		
Heat Pump 3	9,67		
Air Handling Unit	17,79	17,55	1,35
Distribution Pumps	69,64	63,63	8,63
Electronic Equipment	65,77	63,43	3,56
Lighting	12,03	11,89	1,16
TOTAL	200,64	192,88	3,82

As it can be observed in table 2, the estimation of the electrical consumption from the different sources falls within the margin of 10%, as suggested by ASHRAE [15]. Therefore, for the purpose of a parametric variation using P+C, the model was considered accurate enough. As shown by Papas et al [14], several strategies for reducing the energy consumption of ADREAM were evaluated. As concluded, the replacement of the constant flow distribution pumps by variable flow ones could lead to energy gains of around 20% on the total energy consumption.

IV. "BLACK BOX" MODELING

A. Principles

For very complex systems and interactions, such as the ones corresponding to the building ADREAM, it is often useful to use a "Black Box" modeling method [17]. This method provides the capacity to predict the data stemming

from the production and consumption elements (heat pump water temperatures, power consumption, etc.) for the purpose of evaluating different control strategies. A “Black Box” model can be produced through different types of estimation (polynomial, linear, non-linear, auto-regressive with external inputs, state space, transfer functions). MatLab provides the capacity to construct a fitting model through any of the above methods according to the nature of the data.

Since the objective of this project is the energy consumption optimization of the building, after having an initial global assessment through the completion of the DTS, the focus turned on the detailed modeling of all the energy systems. Currently, as the heat pumps are the most crucial element involved in heating and cooling the building, their modeling was prioritized. Accurate model calibrations can be achieved with several options, but since the data concerns a dynamic time-series, a state space function estimation was chosen.

B. Methodology and Results

The “Black Box” process approximates the physical equations governing the interaction of the energetic systems by applying linear differential equations which associate a specific output to a finite number of past inputs and outputs. For the modeling of the heat pumps the input values used were the Electrical Power of the Heat Pumps, and the Return Water Temperature, while the output used was the Produced Water Temperature. The purpose behind the use of these variables has to do with the fact that they all depend on each other. At the same time, by studying the evolution of the water temperature, the estimation of the total electrical power consumption can be deduced. Figure 5 compares the state space model output with the measured data for the produced water temperature.

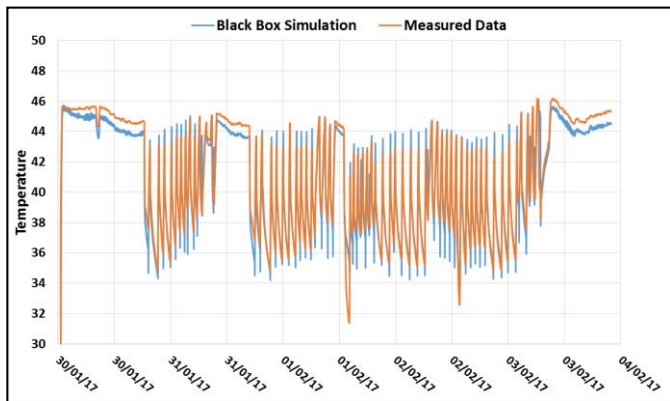


Fig. 5. Black Box Model validation for the Hot Water Temperature produced by the Heat Pumps

As it can be observed, the two curves show a strong fit. The statistical indicators corresponding to this model output as compared to the real data, are: $NMBE = -0.62\%$ and $CV(RMSE) = 1.90\%$.

Since the purpose of this study is the development of a global model that has the ability to predict power consumption through valid simulated data, independent of the registered data, it is essential to produce the input of the return temperature as a model. Thus, a model for the return temperature can be obtained by simulating the effect of the building on the produced water temperature, having the input and output reversed. This process creates a “Black Box”

model representing the building. Figure 6 compares the model output of the return water temperature and the real data.

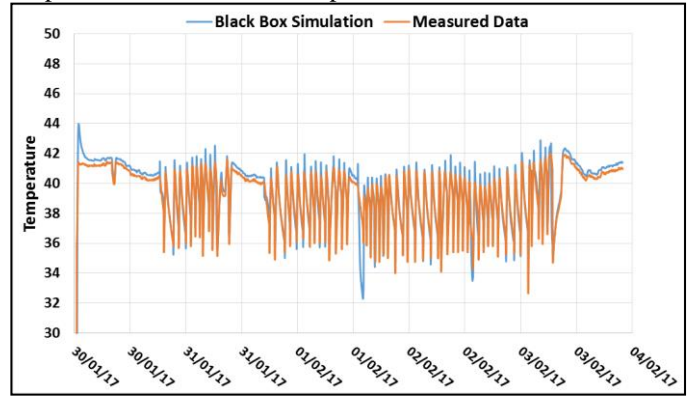


Fig. 6. Black Box Model validation for the Hot Water Temperature returning towards the Heat Pumps

Similarly to the previous model, the return water temperature model has a strong fit with the measured data. The statistical indicators corresponding to this model are: $NMBE = 0.23\%$ and $CV(RMSE) = 1.93\%$.

As of now, prior to advancing to the modeling of the rest of the systems, this method is applied on the functioning of the heat pumps with the aim of optimizing their control. The results obtained from the prediction of the output temperatures consequently provide the equivalent power consumption. The next step of this work requires the determination of the most optimal control for the output water temperatures according to Figure 5.

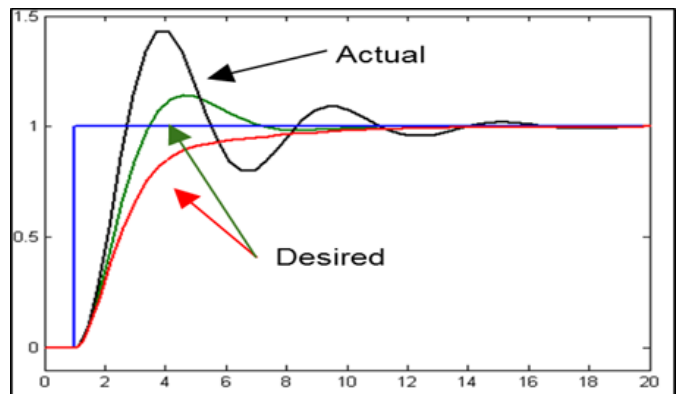


Fig. 7. Control strategies explored for the optimization of the heat pump output temperatures

V. DYNAMIC NEURAL NETWORK MODELING

For similar reasons of system modeling complexity, Dynamic Neural Networks provide a robust solution to the problem of energy consumption prediction. The exploration of this method is at an early stage for the development of a global model where all the installed energy systems interact with each other. The goal is to predict the electrical consumption of heating and cooling in accordance to room temperature set points and weather data. A validated model can provide the capacity to exploit a predictive controller for minimizing energy consumption [18] [19].

The motivation for exploiting Dynamic Neural Network capacities arises from the fact that when the two previous

models are simulated to interact with each other, the continuous iterations produce a large error for the desired outputs, even if the separate models are very accurate individually. Thus, in order to develop a robust simulated input for the returning water temperature, MatLab's Neural Network features were exploited.

A dynamic non-linear filtering was implemented (similarly as for the Black Box modeling) for the prediction of the return water temperature based on its past outputs and on the produced water temperature inputs. The method used is that of the Non-Linear Autoregressive Model with External Inputs (NARX), where an output $y(t)$ is predicted for a given d amount of past $y(t)$ and $x(t)$ values. Equation 3 represents the NARX model applied.

$$y(t) = f(x(t-1), \dots, x(t-d), y(t-1), \dots, y(t-d)) \quad (3)$$

Where:

$y(t)$ = Return Water Temperature [°C]

$x(t)$ = Produced Water Temperature [°C]

d = Sample data

By building and training the model, an output for the water temperature is compared to the measured data as shown in Figure 8.

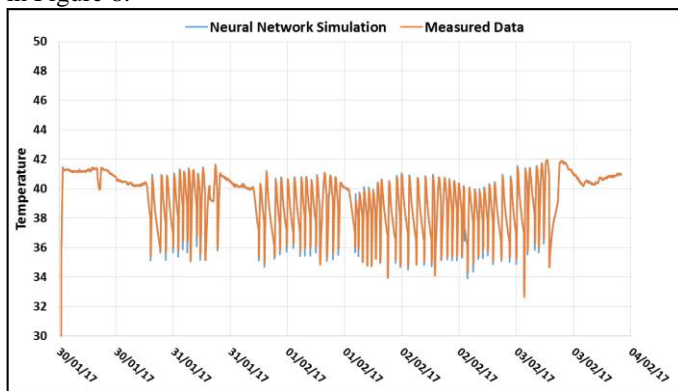


Fig. 8. Dynamic Neural Network Model validation for the Hot Water Temperature returning towards the Heat Pumps

As it can be observed, the fit between model and measured data seems almost perfect. The statistical indicators corresponding to this correlation are: NMBE = 0% and CV(RMSE) = 1.53%. The development of such a precise model is due to the fact that the algorithm is improved through the “feeding” of the past outputs during the training of the network [20].

VI. EVALUATION AND CONCLUSION

The DTS performed on ADREAM provided an initial energy assessment of the building and consisted as the base for the development of an improvement strategy for the current systems installed. More specifically, the accurate electrical consumption prediction of the different sources provided the capacity to simulate various scenarios for optimizing consumption. Thus, recently the old distribution pumps were replaced with variable flow pumps which can potentially reduce electrical consumption by 20%. The measured data a year after this renovation will provide further

insight on the actual energy gain compared to the simulated one.

At the same time, since ADREAM is considered a smart building, additional modeling techniques are being explored for developing more efficient control strategies, exploiting the capacities of the supervision system, while relying on the data of the integrated sensors. The “Black Box” modeling method is capable of simulating very accurate system outputs that can be used as blocks in a global Simulink model which simulates the functioning and interactions of all the associated elements. However, the errors produced through the iteration of models with depended variables required the development of a Dynamic Neural Network model that behaves more robustly when added to the global model. As shown in Section V, the NARX model consists of a promising first step towards the elimination of the errors as the statistical indicators improved vastly through this method in comparison with the simple Black Box modeling.

Future work involves the simulation of a global Simulink model including the heat pump and the building model. Further work will incorporate all the energy systems installed in ADREAM, the calibration and the assessment of their interaction in accordance with the established configuration, and eventually, the exploration of more efficient control strategies for the optimization of the electrical energy consumption through an intelligent management of energy. The practices involved in the improvement of Energy Networks within buildings consist of the first step towards the development of Smart Grids on city scales.

REFERENCES

- [1] <http://ec.europa.eu/energy/en/topics/energy-strategy/2030-energy-strategy> (accessed 21.01.2017).
- [2] P. Torcellini, S. Pless, and M. Deru, D. Crawley, “Zero Energy Buildings: A Critical Look at the Definition”. Preprint NREL ACEEE Summer Study Pacific Grove, California August 14–18, 2006.
- [3] Anna Joanna Marszal, Per Heiselberg « A literature review of Zero Energy Building (ZEB) definitions ». December 2009© Aalborg University. ISSN 1901-726X. DCE Technical Report No. 78.
- [4] A.J. Marszal, P. Heiselberg, J. S. Bourrelle, E. Musall, K. Voss, A. Napolitano. « Zero Energy Building – A review of definitions and calculation methodologies » Energy and Building (2011)
- [5] L Wang, J Gwilliam, P Jones, “Case study of zero energy house design in UK”, Energy and buildings 41 (2009) 1215-1222
- [6] Isa, N. B. M., Wei, T. C., & Yatim, A. H. M., Smart grid technology: Communications, power electronics and control system, Sustainable Energy Engineering and Application, International Conference (2015) 10-14.
- [7] Mohamed, M. A., Eltamaly, A. M., Farh, H. M., & Alolah, A. I., Energy management and renewable energy integration in smart grid system. Smart Energy Grid Engineering (SEGE), 2015 IEEE International Conference (2015) pp. 1-6.
- [8] Solaris Positive Energy, Solaris Concept: The first reproducible green office building with positive energy, (2012) <<http://www.solaris-energie-positive.com/solaris-positive-energy-saving-positive-energy-building.php>>.
- [9] Randall, T., The Smartest Building in the World: Inside the Connected Future of Architecture, (2015) <<http://www.bloomberg.com/features/2015-the-edge-the-worlds-greenest-building/>>.
- [10] <https://www.laas.fr/public/en/adream>.
- [11] PCVue Solutions, <<http://www.pcvuesolutions.com>>.

- [12] Izuba Energies, Pleiades+Comfie, <<http://www.izuba.fr/logiciel/comfie>>.
- [13] B. Peuportier, Bancs d'essais de logiciels de simulation thermique, Journée Thématique SFT-IBPSA (2005).
- [14] I. Papas, C. García Rodríguez, B. Estibals; C. Ecrepont, C. Alonso, "ADREAM:Energy Consumption Optimisation through Dynamic Energetic Simulations for an Intelligent Management of Energy", 2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress, p 975 – 983.
- [15] ASHRAE, ASHRAE Guideline 14-2002, Measurement of Energy and Demand Savings, ASHRAE, Atlanta, 2002.
- [16] A.T. Nguyen, S. Reiter, An investigation on thermal performance of a low cost apartment in hot humid climate of Danang, *Energy and Buildings* 47 (2012) 237-246
- [17] System Identification Toolbox – ARX Models. <<http://www.rohan.sdsu.edu/doc/matlab/toolbox/ident/ch2gui20.html>>.
- [18] T. Salque, D. Marchio, Development of a Neural Network-based Building Model and Application to Geothermal Heat Pumps Predictive Control, *SIMUL 2012: The Fourth International Conference on Advances in System Simulation* (2012) 24-29.
- [19] G. Xu, A. Kusiak, Modeling and optimization of HVAC systems using a dynamic neural network. *Energy* 42 (2012) 241-250.
- [20] <https://fr.mathworks.com/help/nnet/ug/design-time-series-narx-feedback-neural-networks.html>.