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BUILDING ENERGY PERFORMANCE CHARACTERISATION BASED ON DYNAMIC ANALYSIS AND CO-HEATING TEST

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ABSTRACT

A demonstration zero-carbon neighborhood is being raised in the city of Kortrijk, Belgium in the framework of the ECO-Life project within the CONCERTO initiative. A holistic approach is applied to achieve the zero-carbon targets, considering all aspects that are relevant for energy supply. Accordingly, alongside the integration of renewable energy sources in the community, a low-temperature district heating system is being implemented to cover the heat demand. In this context, full scale testing of building thermal performances, by use of a co-heating test and flux measurements, can be useful to analyze the thermal performance of the building envelope in situ. For that reason, as part of a more general study regarding low-energy building, co-heating test, blower-door test and flux measurements in several apartments were executed. Therefore, the paper focuses on characterization of the thermal dynamic behavior of an apartment, as a first approximation of data analysis of a monitoring system involving whole buildings. In addition, in the present study, the capability of linear regression techniques to characterize the thermal behavior of a newly built low-energy apartment in Belgium is investigated. The strengths and weaknesses of different models are identified. The limitation and possibilities of regression models are evaluated in the face of their applicability as a simplified building equation model. The identified model structure is going to be used within a complex simulation model of an entire district heating system with around 200 dwelling. Finally, the potential of this kind of regression models to be used as part of the operational control scheme of a district heating system is presented.

KEY WORDS: Low energy building, Co-heating test, Monitoring analysis

CARACTERIZACIÓN DE LA EFICIENCIA ENERGÉTICA DE EDIFICACCIONES BASADO EN ANÁLISIS DINÁMICO Y EXPERIMENTO A ESCALA REAL “CO-HEATING”

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RESUMEN

Una comunidad demostrativa con cero balance de emisiones de carbono se está construyendo en la ciudad de Kortrijk, Bélgica, en el marco del proyecto ECO-Life dentro de la iniciativa CONCERTO. En el caso de estudio se aplica un enfoque integral para lograr los objetivos de emisión de carbono cero, teniendo en cuenta todos los aspectos que son relevantes para el abastecimiento energético. En consecuencia, junto a la integración de las energías renovables en la comunidad, un sistema centralizado de calefacción urbana de baja temperatura está siendo implementado para cubrir la demanda de calor. En este contexto, las pruebas a escala completa de las prestaciones térmicas de las edificaciones, mediante el uso de técnicas como calentamiento controlado (co-heating) y las mediciones de flujo, puede ser útil para analizar el rendimiento térmico de las edificaciones in situ. Por ello, como parte de un estudio más general concernientes a construcciones de bajo consumo de energía, varios experimentos a escala real fueron ejecutados en varios apartamentos. El documento se centra en la caracterización del comportamiento dinámico térmico de un apartamento, como una primera aproximación de análisis de datos de un sistema de monitoreo que toma en cuenta toda la comunidad. Además, en el presente estudio, la capacidad de las técnicas de regresión lineal para caracterizar el comportamiento térmico de un apartamento de nueva construcción de bajo consumo energético en Bélgica es investigado. Se identifican las fortalezas y debilidades de los diferentes modelos. Las limitaciones y posibilidades de modelos de regresión se evalúan en vista de su aplicabilidad como un modelo simplificado de las edificaciones. La estructura del modelo identificado se utilizará dentro de un complejo modelo de simulación de un sistema de centralizado de calefacción de distrito que cuenta aproximadamente con 200 viviendas. Finalmente, se presenta el potencial de este tipo de modelos de regresión para ser utilizados como parte del esquema de control operacional de un sistema de centralizado calefacción de distrito.

PALABRAS CLAVES: Edificios de bajo consumo energético, Co-heating, análisis de datos energéticos

1. INTRODUCTION

In terms of resource exploitation, the sustainability of energy utilization suggests that the satisfaction of present energy consumption should consider the energy requirements of the future. Furthermore, the energy sector is central in sustainable development and it affects all aspects of development – social, economic and environmental. Accordingly, a sustainable energy system is usually defined in terms of energy efficiency, reliability and environmental impacts. During the last years, in much of the countries, in the current evolution towards renewable energy supply, low energy building are seen as a promising solution. Consequently, in the framework of the ECO-Life project within the CONCERTO initiative, a demonstration zero-carbon neighborhood is being raised in the city of Kortrijk in Belgium.

In this context, full scale testing of building thermal performances, by use of a co-heating test and flux measurements, can be useful to analyze the thermal performance of the building envelope in situ. For that reason, as part of a more general study regarding low-energy building, co-heating test, blower-door test and flux measurements in several apartments were executed. Therefore, the paper focuses on characterization of the thermal dynamic behavior of an apartment, as a first approximation of data analysis of a monitoring system involving whole buildings. Recent works undertaken by several authors indicates that there can be a considerable gap between the U values that are achieved in practice and those that are calculated [1]-[3]. Thus, very little conclusions can be drawn from in-use monitoring studies unless the performance of the building fabric is understood. Therefore, it is crucial that we increase our understanding of how the building fabric performs, the factors that influence its performance and how these factors relate to construction technology, and the design and construction processes. This can only be achieved by measuring and analyzing the performance of the building fabric as built.

Consequently, in the present study the capability of linear regression techniques, to characterize the thermal behavior of a newly built low-energy apartment in Belgium is investigated. The study focuses on characterization of the thermal dynamic behavior of an apartment, as a first step of a data analysis of monitoring system involving whole buildings. For reducing time and complexity a co-heating test was carried out. The co-heating test is used to determine the heat loss by means of air infiltration and fabric transmission of an unoccupied building. The overall heat losses of the dwelling can be seen as a steady state performance. To avoid the thermal inertia influence, the analysis is usually carried out by taking daily averages of the measuring data. However, if the accuracy of the result could be guaranteed, the use of small time step can contribute to reduce the total experimental period. Therefore, in the present study the impact on the results when the amount of descriptive data points is increased by using shorter time step intervals is investigated. The thermal dynamic characterization of the dwelling is assessed by using several parameters such as weather (outdoor temperature, relative humidity, wind speed and solar radiation), building heating energy consumption, indoor temperature, relative humidity and surface temperature by steps of 15 minutes, one hour and 6 hours average values.

2. RESIDENTIAL ZERO-CARBON NEIGHBORHOOD

Following paragraphs, based on reference [4], summarizes the mains characteristic of the exemplary sustainable and zero-carbon neighborhood in the social housing community of Venning site in Kortrijk, Belgium. The implemented residential zero-carbon neighborhood consists of 196 residential dwelling based on different architectural types of low energy dwellings. Despite the conceptual definition provide by the Energy

Performance of Building Directive of the European Union: a 'nearly zero-energy building' is "*a building that has a very high energy performance. The nearly zero-energy or very low amount of energy required should be covered to a significant extent by energy from renewable sources, including energy from renewable sources produced on-site or nearby"* [5]. The target of the ECO-Life project is to establish zero-carbon neighborhoods translated into a clear definition and a number of characteristics and requirements. In a zero-carbon neighborhood the energy use is covered or compensated by energy generated in the neighborhood from sustainable zero-carbon energy sources. The metric of the balance is CO2-equivalents and the balancing period is one year. This means that the net amount of CO2-equivalents released on a yearly basis should be zero.

Even before the design process, the project started with a sustainability assessment of the new building site or the existing neighbourhood that are being improved. This was done through an audit by use of the applicable parts of the monitor plan. The monitor plan for sustainable social housing projects was developed in the ECO-Life project and applied to the Venning neighbourhood at the very start of the project. The plan is used as a guideline and working instrument to translate the sustainability ambitions for the patrimony of the social housing company into practice. Therefore the ambitions were translated into aspired scores in the monitor plan.

Regarding the energy demand of the neighborhood, the balance includes all energy use for space heating, space cooling, hot tap water, auxiliary energy and the energy use for collective functions such as elevators and outdoor lighting in the entire neighborhood. The household energy use of the individual households is not taken into the balance. The energy use is constrained through requirements for energy efficiency, and comfort and indoor climate are considered. The buildings should comply with the Flemish regulation on energy performance and indoor climate, and the passive house requirements are taken as a guideline to reduce the energy demand for space heating and cooling drastically.

The principal site of the project is the Venning neighborhood, which originally consisted of about 163 single-family houses and will count 196 dwellings in single- and multi-family buildings after the project has finished. The Venning will then be a first zero-carbon neighborhood in the patrimony of the social housing company. The full scale test presented on this study is part of a more general research concerning low temperature district heating systems implemented in the demonstration case of zero-carbon neighborhood. A holistic approach is applied to achieve the zero-carbon targets, considering all relevant aspects for energy supply. Figure 1 presents an overview of the district heating layout, construction process and different full scale test carried out in the ongoing project.

Figure 1: Overview of Venning neighborhood and different undertaking activities on the ongoing project.

Alongside the integration of renewable energy sources in the community, a low-temperature district heating is being implemented. Optimizing the system's operation so that efficiency is maximized over a time horizon of several hours, requires prior knowledge of the conditions under which the system will operate at each instance in time during that span, i.e., a load forecast. However load forecasting for large-scale energy systems, such as a neighborhood with about 196 dwellings, requires models that represent the complex relationships between inputs (such as weather or occupancy) and the output (the load).

As have been widely demonstrated first-principles models are generally not practical for this task as they require detailed models of each building and component in the system [6]-[8]. Instead, data-driven, empirical models can capture these complex relationships with reasonably less information about the system. However, the model structure and the suitable inputs must be carefully selected, since empirical models do not always represent the physics in the system. Moreover, model parameters must also be appropriately identified using an adequate amount of historical data from the system. For that reason the work is also devote to identify model structure and parameter treatment to be introduced in a more elaborated load forecasting model for a large-scale energy systems.

3. EXPERIMENTAL BOUNDARY CONDITIONS

The coheating test is used to determine the heat loss by means of background ventilation and fabric of an unoccupied building. The results should usually be delivered in the form of a graph to derive a static value in W/K. As illustrates figure 2, the slope of the regression line resulting from a simple linear regression on corrected or not measurement data set give an indication of the overall heat loss coefficient [9].

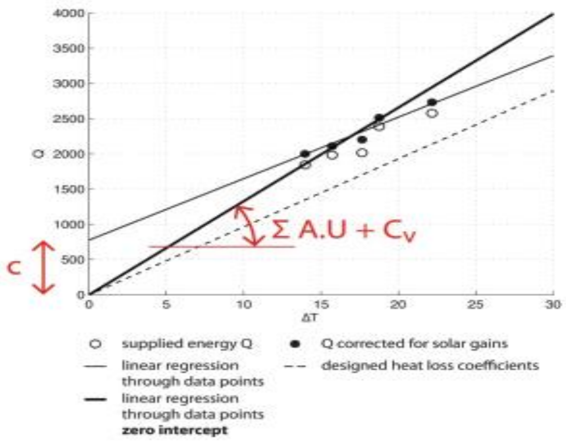


Figure 2: Graphic result of heat loss estimation by simple regression of coheating test measurements

These information can be useful to compare buildings in order to determine best practices or benchmarks. As was observed by Johnston et.al , the coheating test is designed to determine the heat loss coefficient by measuring other factors [10]. The analysis are usually based on Eq. (1), which shows the heat balance of a dwelling. With Q_{in} power supplied by the electrical heater (*W*), Q_s solar gain (*W*), *U* mean U-value of the fabric (W/m^2K), *A* surface area of the fabric (m^2), C_v infiltration heat loss coefficient (*W/K*), *H* transmission heat loss coefficient (*W/K*) and ΔT the temperature difference between inside and outside (*K*).

$$Q_{in} + Q_s = (\sum UA + C_v)\Delta T = H\Delta T + C_v\Delta T \qquad (1)$$

Following paragraphs summarizes the experimental conditions. A co-heating test was carried out at the Kortrijk municipality, in Belgium. The experiments were performed over period of 20 days, starting the 15th of April 2013 and ending the 5th of May 2013. The investigated case consists of a low-energy apartment (see figure 3) with 1,9 kW design heat losses at the winter design ambient temperature of -8°C. It corresponds to a family house for 3 people living in Belgium : 89 m² of living surface.

Figure 3: The low-energy apartment investigated

The equipment deployed within the tested building includes convertor connected to thermostats, axial fans to agitate the air, heat flux loggers and temperature and relative humidity sensors, which are all spaced evenly throughout the property. Their electricity consumption has been recorded by pulse/kWh meters. Weather conditions have been monitored by an external temperature and relative humidity sensor, and pyranometer that are installed outside. Figure 4 shows a plant view of the apartment with the distribution of the equipment used in the testing houses.

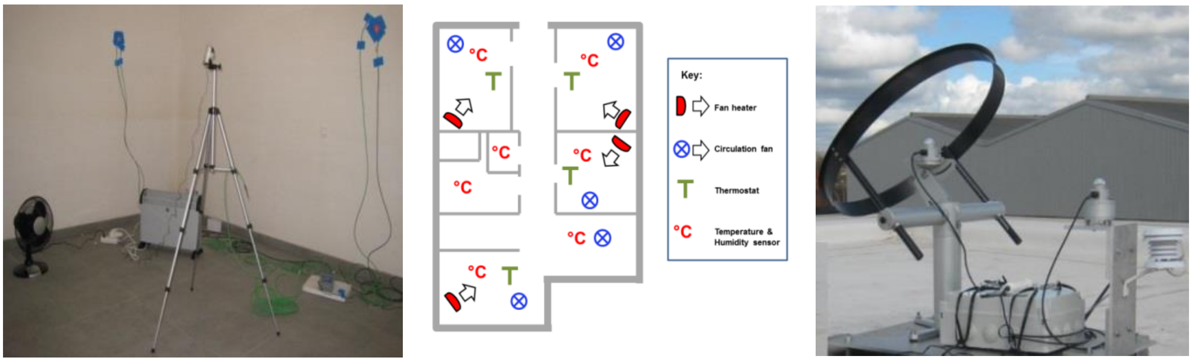


Figure 4: Devices deployed for the co-heating test

Wind speed was obtained from another nearby weather station. Once equipment were installed and operating, the thermostats were all set to a desired temperature, nominally 25°C, however to warrantee a difference of 10 °C with the outdoor temperature the thermostat set point was at 35 °C. The equipment continually records all the readings for relative humidity, temperature (internal/external), energy use, and solar irradiance.

The period of monitoring is 20 days, which requires an initial 5 days of set up and time for internal temperature to stabilize. Figure 5 displays the measured data during the experimental period. The graphic shows a small part of the 5 days needed from the start of the tests to approach stability. These five days were excluded from the analysis. There are several periods where solar gains appear to displace heating for several hours. In addition, it can be seen that during the whole period only one hour reach a minimum value of temperature difference of 7 °C degree. The maximum value of temperature difference was 30.5 °C degree while the average temperature difference was 22 °C.

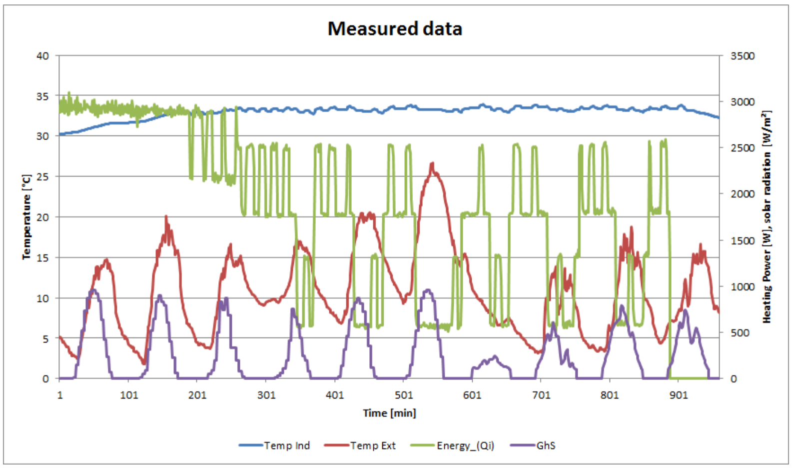


Figure 5: Measured data during the experimental period.

4. ANALYSIS BASED ON ENERGY BALANCE

One of the main aims of full scale experiments is to investigate whether it is possible to characterize the dynamic behavior of the indoor conditions of a dwelling based on the measured data of the experiment.

Considering as much as possible the different terms involved in the energy balance of a building, the previous expression is extended. The variation of internal energy *E(J)* of the rooms, represented by the left hand side of Eq. (2) can be related with heating or cooling by HVAC systems or an auxiliary equipment (for instance fan heater), Q_{in} *(W)*, a convective heat flow due to ventilation Q_v(*W*), a convective heat flow due to infiltration by wind and stack pressure effect Q_{inf} (*W*), the heat gain due to solar radiation Q_s and the convective heat transfer with the building envelope surfaces Q_t(*W*), all shown in the right-hand side of Eq. (2) [11].

In addition, it is well-known that the interior climate conditions depend not only on the heat flux through the envelope (transmission, solar input, internal thermal loads and sensible gain of the air exchange), but also, internal latent losses as a result of air exchange due to natural convection or HVAC systems must be taken into account. In addition, in Eq.(2) C_b (*J/K*) as the overall thermal capacitance and the co-heating test conditions (unoccupied building and ventilation system off) have been included. Besides, in the case of a well-controlled co-heating test, changes of air humidity are caused only by infiltration and moisture contained by interior surfaces. Thus the energy balance can be described with the following expression.

$$\frac{dE}{dt} = C_b \frac{dT_t}{dt} = Q_{in} - H\Delta T - Q_{inf} + Q_s - Q_{ev} \tag{2}$$

Following, a basic definition of the terms of the above expression is presented. The influence of the infiltration, based on [12] is defined. In Eq. (3), d_w is the experimental coefficient that is representative of infiltrations due to wind, v is the wind speed (*m/s*) and n = 2/3 is the coefficient that reflects to the shape of crack through the envelop.

$$Q_{inf} = C_v \Delta T = d_w v^{4/3} \Delta T \tag{3}$$

Water vapor migrates by diffusion through air and building materials, normally in very small quantities. However, diffusion becomes more important with increasingly airtight construction. The latent heat required for vaporization is taken up partly from the surroundings, thus causes cooling. Considering h_{fg} as latent heat of evaporation at indoor air temperature in (*J/kg*), G_{wj} as the rate of evaporation in (*kg/s*), A_j surface area (*m²*) and g_w the moisture flux from the interior surface into the room (*kg/[sm^2]*). A simplified estimation of the latent heat influence accompanying moisture transfer through walls can be computed by

$$Q_{ev} = h_{fg} G_w = h_{fg} \sum_j A_j \, g_w \tag{4}$$

The moisture flux can be estimated by the following expression.

$$g_w = \frac{G_w}{\sum_j A_j} = \frac{P_{w,s} - \varphi P_{w,s}}{Z} \tag{5}$$

With A_j surface area (*m²*), $P_{w,s}$ saturation pressure of water vapor (*Pa*), φ relative humidity of the room (*%*) and Z the diffusion resistance. To estimate the diffusion resistance, a surface transfer coefficient (β_s) equal to 18x10^{-9} s/m is used. The saturation pressure of the water vapor in moist air varies with the temperature of the air vapor mixture, T, and as was reported by Hens in [13] can be expressed as:

$$P_{w,s} = exp\left(65.8094 - \frac{7066.27}{273.15+T} - 5.976\, ln(273.15+T)\right) \tag{6}$$

In addition, a better treatment of the overall heat load influence can be done. By differentiating between the dynamic of the indoor air and the slow dynamics of the building structure. Considering surface temperature both wall to the indoor and to the outdoor environment. Assuming C_w (*J/K*) as the thermal capacitance of the wall and taking into account Eq.(7)- Eq.(9):

$$C_b \frac{dT_i}{dt} = \frac{1}{\frac{1}{H} - \frac{1}{H_w}}(T_w - T_i) + H_{gl}\Delta T + H_{wi}(T_{wi} - T_i) - d_w v^{\frac{4}{3}}\Delta T + f_2 Q_{in} + Abs_2 Q_s \tag{7}$$

$$C_w \frac{dT_w}{dt} = \frac{1}{\frac{1}{H} - \frac{1}{H_w}}(T_i - T_w) + H_w(T_e - T_w) + f_1 Q_{in} + Abs_1 Q_s - h_{fg} \sum_j A_j \, g_w \tag{8}$$

$$C_{wi}\frac{dT_{wi}}{dt} = H_{wi}(T_{wi} - T_i) \tag{9}$$

In the above expressions A_w is the wall surface area (m^2), h_w and h_{wi} in ($W/[m^2K]$), are the total surface heat transfer coefficient of the wall to the outdoor and indoor environment respectively , T_w is the surface temperature of the outdoor walls, T_{wi} is the surface temperature of the indoor walls, *f* and *Abs* are respectively weighted factors of the heating and the solar gain accounting for the radiant fraction of the internal gain absorbed directly by the walls; while T_e is the outdoor temperature and T_i the indoor temperature. Furthermore, a distinction between the influence of the overall heat losses through opaque wall ($H_w=h_wA$ and $H_{wi}=h_{wi}A_i$), as well as the overall heat losses through the windows (H_{gl}) have been considered. Introducing all the specific parameters for each term in Eq. (2), the following model structures can be obtained. In Eq (10) I_s represents the solar irradiance on the horizontal, while *gA* represents the solar aperture of the dwelling.

$$Q_{in} = H_w(T_w - T_e) + H_{gl}\Delta T - gAI_s - d_w v^{\frac{4}{3}}\Delta T - h_{fg}\sum_j A_j\, g_w + C_b\frac{dT_t}{dt} + C_{wi}\frac{dT_{wi}}{dt} - C_w\frac{dT_w}{dt} \tag{10}$$

5. REGRESSION ANALYSIS CONSIDERATION

In order to obtain the coefficients, by considering the model defined in Eq. (10), multiple regression analysis were performed. In multiple regression there is one variable to be forecast (dependent variable) and several predictor variables (independent variables). The coefficients of predictor measure the effect of each independent variable after taking account the effect of all other variables in the model [14].

When applying both multiple regression or simple linear regression, we require the following assumptions for the errors (e_1 ,…, e_n): a) the errors have mean zero, b) the errors are uncorrelated with each other and c) the errors are uncorrelated with each predictor $x_{j,i}$. In order to develop the regression model the values of the coefficients β_0 ,…, β_k are obtained by finding the minimum sum of squares of the errors. This is called "ordinary least squares" estimation because it the least value of the sum of squared errors. As was aforementioned, the residuals has zero mean and are uncorrelated with any of the predictors. Finding the best estimates of the coefficients is often called "fitting" the model to the data. That is, we find the values of β_0 ,…, β_k which minimize.

$$\sum e_i^2 = \sum\left(y_i - \beta_0 - \beta_1 x_{1,i} - \beta_2 x_{2,i} - \cdots - \beta_k x_{k,i}\right)^2 \tag{11}$$

Moreover, it is important to measure the predictive accuracy of the model. Computer output for regression will always give the well-known R^2 value [14]. Residual diagnostic becomes another important task when defining the predictive ability of a model, in order to evaluate if the model violates the assumption of no autocorrelation in the errors. A statistical test that is designed to analyze the autocorrelation of the regression model is the Durbin-Watson test (*d*) . This statistic tests the residuals to determine if there is any significant correlation based on the order in which they occur in the data. As a rough rule of thumb, if *d* statistic is less than 2, indicate successive error terms are positively correlated. If e_i is the residual associated with the observation at time *t*, then the Durbin-Watson statistic tests is:

$$d = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \tag{12}$$

6. MODELING BY USING REGRESSION ANALYSIS

In this section several models using different combination of the input variables and time step of 15 minutes, one hour and 6 hours were investigated. All variables were introduced according to the energy balance presented from Eq. (1) to Eq. (10) see table 1.

Chart 1: Variables considered in the models

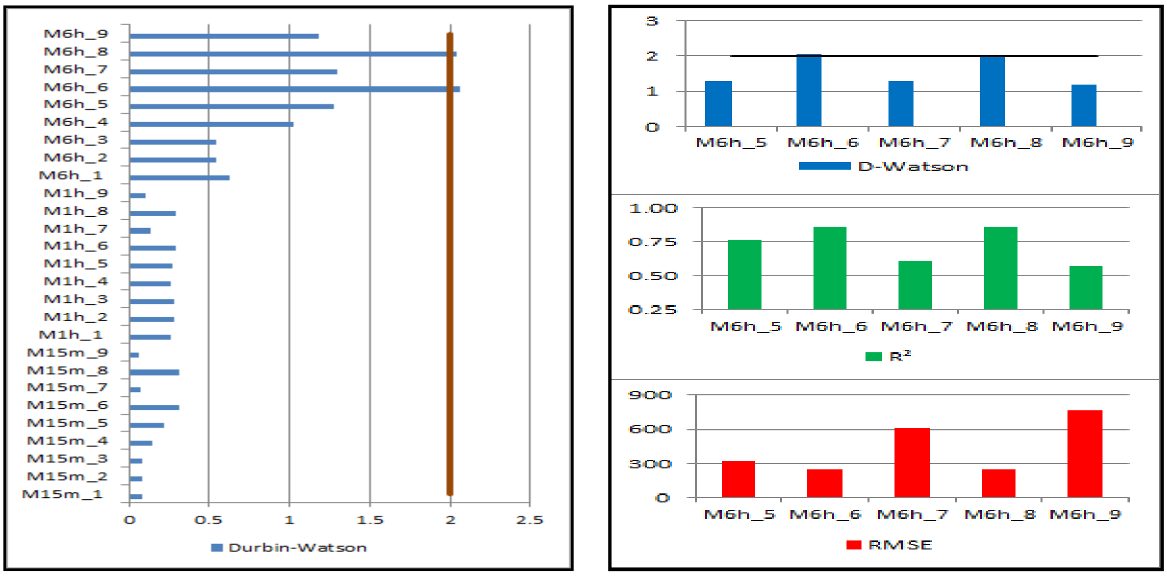
Variables	Model Name			Models
	15 minutes	1 hour	6 hours	
T_e,T_i	M15m_1	M1h_1	M6h_1	$Q_{in} = H\Delta T + C_v\Delta T$
T_e,T_i,I_s	M15m_2	M1h_2	M6h_2	$Q_{in} = H\Delta T + C_v\Delta T - Q_s$
T_e,T_i, I_s,v	M15m_3	M1h_3	M6h_3	$Q_{in} = H\Delta T + Q_{inf} - Q_s$
T_e,T_i, I_s,v,T_{i_1}	M15m_4	M1h_4	M6h_4	$Q_{in} = H\Delta T + Q_{inf} - Q_s + C_b\frac{dT_t}{dt}$
T_e,T_i, I_s,v, T_{i_1}, w,	M15m_5	M1h_5	M6h_5	$C_b\frac{dT_t}{dt} = Q_{in} - H\Delta T - Q_{inf} + Q_s - Q_{ev}$
T_e,T_i, I_s,v, T_{i_1}, w,T_w	M15m_6	M1h_6	M6h_6	$Q_{in} = H_w(T_w - T_e) + H_{gl}\Delta T - gAI_s - d_w v^{\frac{4}{3}}\Delta T - h_{fg}\sum_j A_j g_w + C_b\frac{dT_t}{dt} + c_{wi}\frac{dT_{wi}}{dt} - c_w\frac{dT_w}{dt}$
T_e,T_i, I_s,v, T_{i_1},T_w	M15m_7	M1h_7	M6h_7	$Q_{in} = H_w(T_w - T_e) + H_{gl}\Delta T - gAI_s - d_w v^{\frac{4}{3}}\Delta T + C_b\frac{dT_t}{dt} + c_{wi}\frac{dT_{wi}}{dt} - c_w\frac{dT_w}{dt}$
T_e,T_i, I_s, T_{i_1}, w,T_w	M15m_8	M1h_8	M6h_8	$Q_{in} = H_w(T_w - T_e) + H_{gl}\Delta T - gAI_s - h_{fg}\sum_j A_j g_w + C_b\frac{dT_t}{dt} + c_{wi}\frac{dT_{wi}}{dt} - c_w\frac{dT_w}{dt}$
T_e,T_i, I_s, T_{i_1},T_w	M15m_9	M1h_9	M6h_9	$Q_{in} = H_w(T_w - T_e) + H_{gl}\Delta T - gAI_s + C_b\frac{dT_t}{dt} + c_{wi}\frac{dT_{wi}}{dt} - c_w\frac{dT_w}{dt}$

By using data from 22th April to 25th of April, models were fitted. Model are compared by means of the adjusted R², the root mean square error (RMSE) and the Durbin-Watson statistic. The evaluation serves both to check if the model meet the assumptions and clarify model deficiencies identifying which parts of the model have to be further improved. Table 2 shows the statistic for the case of models with 15 minutes time step.

Chart 2: Statistic for the case of models with 15 minutes time step

Variables	Model Name	Statistic		
	Time step 15 minutes	R^2	RMSE	Durbin-Watson
T_e,T_i	M15m_1	0.28	657	0.08
T_e,T_i,I_s	M15m_2	0.32	637	0.08
T_e,T_i, I_s,v	M15m_3	0.32	636	0.08
T_e,T_i, I_s,v,T_{i_1}	M15m_4	0.45	571	0.14
T_e,T_i, I_s,v, T_{i_1}, w,	M15m_5	0.71	415	0.22
T_e,T_i, I_s,v, T_{i_1}, w,T_w	M15m_6	0.77	372	0.31
T_e,T_i, I_s,v, T_{i_1},T_w	M15m_7	0.51	902	0.07
T_e,T_i, I_s, T_{i_1}, w,T_w	M15m_8	0.77	372	0.31
T_e,T_i, I_s, T_{i_1},T_w	M15m_9	0.54	1117	0.06

Figure 6 presents a summary of statistic parameters of different fitted models. As can be seen only some models using a time step of 6 hours are able to avoid the autoregressive behavior of the residuals. Figure 6 *b)* shows the statistic of those models. Results clearly show that model M6h_6 and M6h_8 presents the better value of Durbin-Watson statistic and both the R square and the RMSE perform better compared to the rest of the selected models. Results denote a significant poor performance of the model from model M6h_1 till model M6h_3. An improvement appear in model M6h_4 and M6h_5 when the indoor temperature of the previous time step and the humidity in the room are include in the model. As expected a significant change happened when surface temperature is include as can be seen in model M6h_6. It should be noticed that model M6h_6 take into account all the variable studied. When comparing the performance of M6h_7 and model M6h_6, a significant decrease of model performance is found. In model M6h_7 the humidity was not included, thus the evaporation losses were not taken into account. Result denotes the impact of this variable in combination with surface temperature. Similar inference can be identified when analyzing model M6h_8 and model M6h_9.



a) b)

Figure 6: Summary of statistic parameters of different fitted models

In addition, the graphic at figure 6 *a)* reflects that models with small time step, i.e 15 minutes and 1 hour presents Durbin-Watson statistic values lower than 2 (reference value). When using small time step the selected independent variables cannot explain satisfactorily the variability of the indoor conditions and the energy demand. The results denote that those models present an autoregressive behavior of the residual. As was previously mentioned, an important implicit assumption of the regression model consists on the independent errors (residual). When residuals are not independent this breaks up the usual assumption made in ordinary least squares regression. The consequence is that the estimates of coefficients and their standard errors are wrong due to the autoregressive structure of the errors.

It is possible to adjust estimated regression coefficients and standard errors when the errors have an autoregressive (AR) structure. In order to improve the model, the Cochrane-Orcutt Estimator procedure to adjust the coefficient of the original regression model can be applied [15]. The Cochrane-Orcutt Estimator aims to create a new estimating equation, transforming the original variables in the process of eliminating or reducing the first order serial correlation.

The aforesaid procedure estimates a AR coefficient by means of regression analysis of the residual of the original model. The slope of the correlation curve between the residual and its previous value represent the Cochrane-Orcutt Estimator " rho" coefficient. Considering Eq. (10) as a linear regression model with a model of a dependent variable Y as a function of a set of independent variables $X_1 \ldots X_k$ with AR errors. The procedure transforms and redefines each variable to the right side of the Eq. (13) and a new regression model Y^* on k^* and the X_i^* , Eq. (14) is obtained.

$$\begin{aligned} Y^* &= Y_t - \rho Y_{t-1} \\ X_i^* &= X_{i,t} - \rho X_{i,t-1} \\ k^* &= 1 - \rho \end{aligned} \tag{13}$$

$$Y^* = b_0 k^* + b_1 X_1^* + b_2 X_2^* + \cdots + u_t \tag{14}$$

As an example, the procedure was applied for model M15m_8 and model M15m_9. For the case of model M15m_8 a convergence of the rho value equal to 0.88 was found. Once the rho coefficient was estimated, the adjustment of regression variables was conducted.

A new model M15m_8A, "M15m_8 with adjusted coefficients" was estimated by using the ordinary least squared regression. Model M15m_8A presents a good correlation factor R^2 equal to 0.96 and the Durbin-Watson statistic is 2.21 while the root mean square error is equal to 155. In order to validate the previous models, the characterization of the dynamic behavior of the dwelling by estimating the indoor room temperature was carried out. By both prediction and cross-validation, the robustness of model M15m_8A is evaluated.

The result of cross-validation of model M15m_8A is shown in figure 7. With cross-validation, we are wanting to predict the value of something we have not observed, using the information on the cases that we have observed [16]. Thus, cross-validation is carried out by performing a 15 minute time step prediction of the indoor temperature for three day of the experimental period, starting at 25th of April 2013 and ending the 29th of April 2013 as well as during the period of free floating from 29th of April till 4th May. Figure 6 shows the correlation between the observed indoor temperature and the predicted value when M15m_8A was applied. As can be seen the model is able to follow the trend of the observed data. Hence the result denotes that the model explains the variability of the indoor temperature conditions and the energy demand of the studied case quite good.

Result demonstrates that the deviation of the observed data remind in a well reasonable upper and lower limit interval. The estimation presents a standard deviation of 0.4°C. Moreover, when using M15m_8A to estimate the indoor temperature, the mean relative error is approximately 0.9% of the real value. Results demonstrates the capability of the model to describe satisfactorily different kinds of experimental conditions. It can be seen that the model estimates correctly the indoor temperature during the last period of the co-heating test, as well as the free floating period from 29 of April till 4 of May .

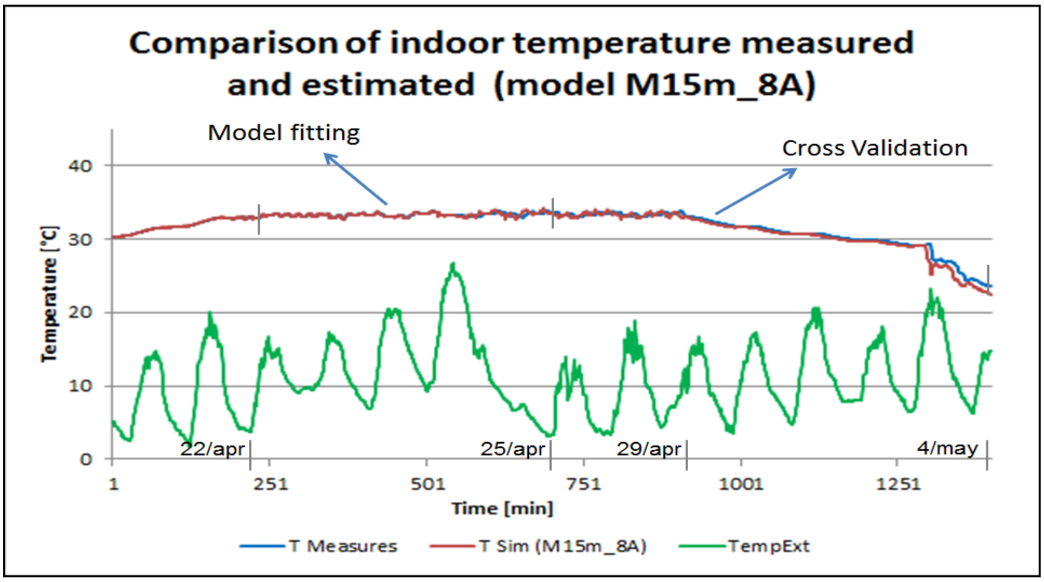


Figure 7: Indoor temperature predicted and Cross-validation with model M15m_8A

As was aforementioned the procedure was also applied for model M15m_9 and a convergence of the rho value equal to 0.93 was found. Figure 8 displays the comparison of measured an estimated value with model M15m_9A (model M15m_9 with adjusted coefficients). The graphic denotes that the model explains the variability of the energy demand and consequently the indoor temperature conditions very well. The correlation factor R^2 presents a high value up to 0.97.

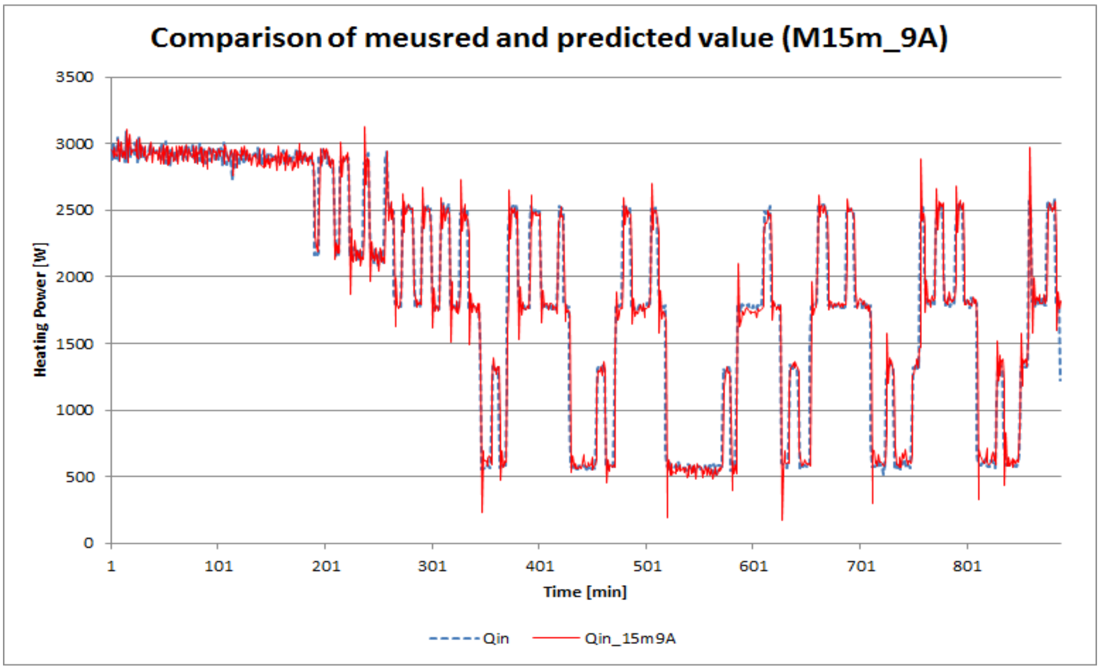


Figure 8: Comparison of measured an estimated value with model M15m_9A

7. FUTURE WORK DIRECTION

In future works we will explore the methodology for load forecasting reported by Ben-Nakhi and Mahmoud in reference [7]. As was observed by the author, a linear model can be identified using inputs such as weather, previous loads, and time variables to represent the hour of the day, day of the week, month, etc. These time variables serve as a proxy for occupancy, which is generally difficult to quantify and predict. Because of the regularity of work schedules and seasonal load variations, occupancy can be represented using different model parameters corresponding to different hours, days, or months. The linear load-forecasting model takes on the form shown in Eq. (15), where a, b, and c are the model fitting coefficients, L_k is the load at time k, N is the model order (i.e. the number of time steps back to retrieve inputs), and θ represents the values of weather variables. The subscripts h, d, and m refer to the hour of the day, day of the week, and month of the year, respectively. Therefore, there are different additive constants (c_h, c_d, and c_m) for each time period.

$$L_k = \sum_{i=1}^{N} a_i L_{k-i} + \sum_{i=0}^{N} b_i \theta_{k-i} + c_{h,k} + c_{d,k} + c_{m,k} + e_i \qquad (15)$$

The relationship in Eq.(15) is an autoregressive model with exogenous inputs (ARX model) and uses past load information to predict future loads, making it recursive in nature. Exogenous inputs such as weather or time can be added to improve model accuracy by representing the dependence of the load on these additional inputs. The model order, N, can be adjusted so that more (or fewer) past states and inputs are used. Noted that the structure of one of the regression model identified from Eq. (1) till Eq (10) will be introduced as the exogenous inputs of the autoregressive model in Eq. (15). In order to consider the nonlinearity in the relationships between inputs and loads, neural networks are a feasible alternative.

8. CONCLUSIONS

In the present study, based on linear regression techniques, the accuracy of the quasi-stationary analysis on the experimental measurement data of the thermal behavior of a low energy apartment was investigated. By means of nine different model the capability of linear regression methods to reach accurate results when using small time step of the experimental data was studied. The study demonstrates that multiple regression model with generalized least square coefficients (adjustments) “M15m_8A and M15m_9A” explains adequately the dynamic behavior of the low energy apartment analyzed. The cross-validation denotes the ability of the model to describe different experimental situation. However, when using small time steps the traditional ordinary least square method in which is based the multiple regression analysis (i.e without to introducing any modification) is not able to provide an accurate result due to the autoregressive behaviors of the residual

In addition model structure and suitable inputs for an empirical models representing as much as possible the physics in the system were verified. Moreover, appropriately model parameters to be introduced in a more elaborated load forecasting model for a large-scale energy systems were also identified. Future work includes developing a dynamic model of the dwelling within the TRNSYS software.

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