Considerations on Energy Consumption Prediction in Residential Sector during the COVID-19 Pandemic Conditions using Artificial Neural Networks

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Abstract: ***After almost twenty years of successful work and promising research in predicting different energy consumptions by developing, training and using artificial neural networks, a new challenge arises in the last two years. The COVID-19 pandemic restrictions and public health measures changed most of the established energy consumption patterns, brought new variables into consideration and took everyone by surprise. The result can be seen in the energy and material crisis that is unfolding as we speak. Our goal in this paper is establishing new ways of approaching public and private energy policies by using machine learning and artificial neural network predictions.***

Keywords: energy consumption, residential sector, artificial neural networks, pandemic, public policy

1. Introduction

As we established in previous published work, using artificial neural networks to predict energy consumption is a viable method and offers more reliable data. The standards that are used today in urban design and energy policies and resources allocation planning are based on a a series of calculations methods and normative values. These values and methods are not actually predictions of energy or resources consumption and we can tell this by the static and rigid aspect of them. They are based on functionality and standard needs and don't take into consideration the dynamic relations between all the variables that come into play and the real energy and resource consumption. The two values can sometimes vary significantly because there are a lot of factors that are not taken into consideration (the human factor for ex.) just because there are no standards for them, we don't know the impact that they have (the rate of unemployment for ex.) or we don't have a linear mathematical relation between them and the final energy consumption value.

Solving some of these problems by using artificial neural networks allows to accurately determining the results almost instantly, without the need to use mathematical modeling of the process and repeating these calculations for new situations [1]. Of course, we do still need most physical parameters of the building, number of occupants and other variables but the results do no longer depend on norms and standards which may not be suitable for our class of buildings. Instead, they rely on real consumption patterns from real cases over the years. The ANN can learn non-linear relations between the parameters and they can determine what kind of influence do they excercit on the result.

In the past published work we built, trained and released different ANN's that could accurately predict energy consumption for different households and urban environments and as long as the parameters stayed between certain limits, the predictions were acceptable.

The COVID-19 restrictions on the other hand brought to the surface other kind of input variables that we could not foreseen in the previous work. So taking into consideration the new variables and understanding how they influence the predicting results in needed. In the current paper we present the process and the findings of this work.

2. Theoretical considerations on Artificial Neural Networks (ANN)

An artificial neural network is defined as an evenly distributed information processor with the ability of experimental data storage and prediction on new input cases. The information processing module mimics the human brain activity forming patterns by studying the existing situations and applying the knowledge to generate predictions about new situations.

ANN's are used in the engineering field as an alternative method of analysis and prediction. Neural networks operate successfully in most cases where conventional methods fail, data analysis being applied at present to solve a variety of nonlinear problems such as pattern recognition. [3]

Instead of using complex rules and mathematical routines, ANN's are able to learn the key information patterns within a multidimensional information domain. In addition, neural networks successfully eliminate data entry errors and supplementary information irrelevant to the processes, becoming robust tools for data modeling and prediction [4].

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3. COVID-19 situation and restriction impact on the energy sector

Before the COVID-19 pandemic, energy efficiency, energy-saving, and new energy solutions are regarded as critical elements to stabilise energy demand. Stabilising energy demand is a key indicator to conserve economic/urban sustainability during and after the pandemic. As the pandemic continues, it is understandably challenging to stabilise and recover the energy demand absolutely. Fig. 2 shows the diagrams of stabilising energy demand under different thinking manners.

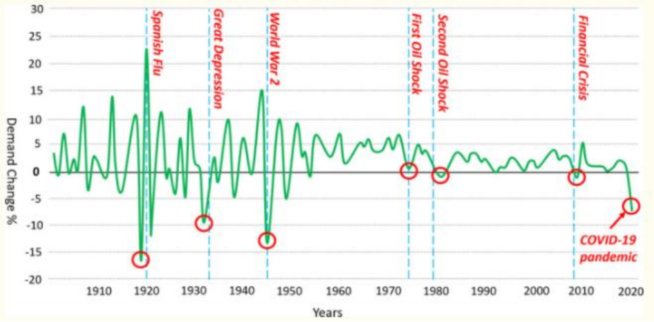

Figure 1: Change on the global energy demand at last century

Several extreme events occurred due to dropped energy demands, such as the negative wholesale power prices in Germany and the negative oil prices in the USA. Global decision-makers were/are proposing emergency measures to conserve energy consumption and subsidise energy producers. Amongst many tricky problems, the issues of energy poverty and energy bill increasesare more urgent than ever in the COVID-19 crisis. Mastropietro et al. compared the global measures from disconnection bans to bills cancellation that were used to protect energy consumers. Brosemer et al. discussed the intersections of indigeneity, inequity, and health. For a better solution, decision-makers should personalise the decisions on subsidies considering the different geographical and sociological factors. Big urban data analytics on household electricity consumption could be employed to offer targeted subsidies. [2]

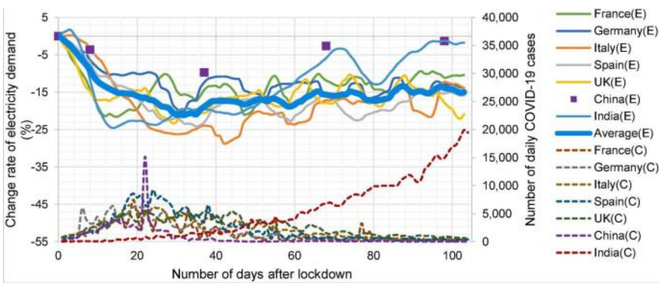

Figure 2: The reduction of daily electricity demand (weather corrected) after implementing lockdown measures and the number of daily COVID-19 cases in selected countries.

The politicians/policymakers always face a dilemma between the lockdown holding to keep people healthy and the lockdown exit to recover the energy and economy. Different governmental policy responses may explain the different magnitudes of impacts. When relaxing or lifting lockdown, along with the re-start of economic activities, the energy demand/consumption in transport, production and services could recover gradually. Fig. 2 shows the reduction of electricity demand and the number of daily COVID-19 cases in selected countries. When the number of daily COVID-19 cases exceeded a certain threshold, policymakers implemented lockdown measures. The reduction rate steeped down sharply after strengthening lockdown measures. During the lockdown period, the number of cases reached a peak and decreased gradually. Policymakers made trade-offs on when to relax measures. [2]

After relaxing lockdown measures, the recovery processes of energy consumption are reflected by the trend lines in Fig. 3. Compared to the five countries in the EU, China, and India presented unique situations. In China, the number of daily COVID-19 cases nearly approached to zero after the lockdown. There was more confidence in society to recover economic activity and energy consumption. In India, although energy consumption nearly returned to normal status as in China, it was at the expense of the increasing number of daily COVID-19 cases. The five countries in the EU presented similar characteristics in terms of the lockdown measures, the trend of daily cases and the relatively slow recovery of energy consumption. The bold line 'average'—namely, the average reduction rate of the five countries in the EU—changes from ~21% (the peak during the lockdown) to ~15% (about two months after relaxing lockdown). The ongoing disease epidemic and partial lockdown/restrictions result in a relatively slow recovery.

The factors which could affect the energy consumption of the comparative options could be summarised as:[2]

- Commuting distance (e.g. if it is a “15 min city”, the energy consumption is less significant) and route (e.g. together with grocery shop on the way home)
- The energy efficiency of buildings (e.g. the lighting, cooling, and heating system of home versus office)
- Occupancy (e.g. home office or e-learning – one person occupied a room)
- The duration of usage (e.g. computers)
- Information and communications technologies to support the digitalisation (e.g. data centre, the demand for equipment)
- Daily activities (e.g. travel as there is no need to attend the office physically)

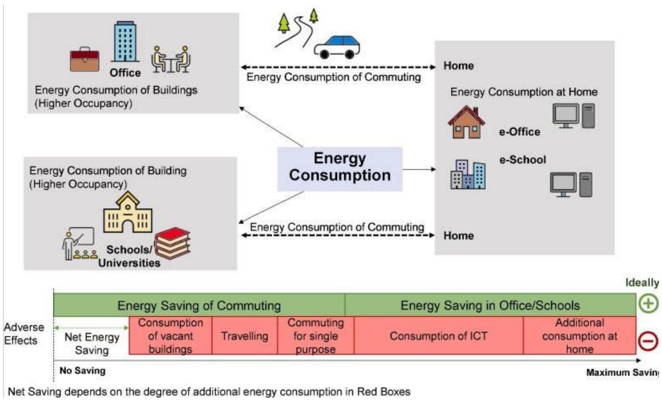

Figure 3: The different sources of energy consumption of physical and virtual schools/offices

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According to the energy consumption in the information technology sector, other than the use of devices (20%), data centres (19%), networks (16%) and computers (17%) are the main sources of energy consumption. The power consumption of ICT activities has been expected to reach close to 40 PWh in 2030. The energy use of global data centres is estimated as 205 TWh (6% increase compared with 2010) in 2018, constitutes 1% global electricity consumption. The CO2 emissions related to artificial intelligence computations are non-negligible nowadays.

Energy storage could mitigate demand variations, enhance the flexibility of energy systems, and enable the dispatching of renewables. The COVID-19 pandemic influences energy storage. Before the COVID-19, due to the uncertainties of battery safety and the unstable policy support in markets, energy storage had been losing momentum as the annual total installations of the energy storage technologies year-on-year in 2019 fell by 20%. In a short-term, COVID-19 changed the economic structure, reduced investment for the energy storage industry, and disrupted the supply chains from cells to installers. Some storage projects were hung on temporarily, which dragged the growth rate of energy storage development. In a long-term, COVID-19 offers opportunities for the energy storage industry. The crisis could trigger energy transitions, including the sustainability transitions, clean energy transitions, and sustainable energy transitions under different politics related to COVID-19, which further offers potential development/opportunities of novel energy storage technologies.

4. The database construction for the ANN's training

The database that will be used to train the neural network must contain enough cases in order for the method to have a general application. Also, the cases should be evenly distributed over the length of analyzed interval, for the level of accuracy in predicting future cases to be as high as possible.

4.1 Selecting the input and output parameters

Given the available data, the following variables are chosen to represent the input parameters of neural network, being the input neurons of the network as well:

- N representing the number of occupants;
- D_{lock} representing the number of days of total lockdown;
- $D_{restrict}$ representing the number of days of movement restrictions (over 10:00 pm or reduced hours;
- S_h representing the total heated area [m^2];
- V representing the volume [m^3];
- $S_{anvelopă}$ representing the total outside surface [m^2];
- $S_{pereți}$ representing the outside wall surface [m^2];
- $S_{terasă}$ representing the terrase surface [m^2];
- $S_{fe.usi}$ representing the total outside windows and doors [m^2];
- $R_{pereți}$ being the thermal resistance of the walls [m²K/W];
- $R_{terasă}$ being the thermal resistance of the terrace [m²K/W];
- $R_{fe.uși}$ being the thermal resistance of the windows and doors, obtained as the ponderate mean regarding the surface [m²K/W]
- T being the average outside temperature mean of that specific month [°C]

The variable chosen to represent the output parameter of the neural network and also the output neuron is:

- Q_h being the annual energy consumption for heating [kWh/year].

4.2 Construction of the ANN's training file

For constructing the database iterative calculations were made for 12 different input parameter measured montly for a period of a year for 70 cases resulting in a number of 840 distinct sets of data.

The values were measured and recorded in Cluj-Napoca, Romania by using the gas and electric meters installed in these householdes.

5. The construction and the training of the ANN

The program MathLAB, was used for the construction of the neural networks, for which an academic license was obtained.

In order to determine the right architecture of the network, a series of trials were made. The final architecture is composed of 14 neurons on the input layer (13 corresponding to the input parameters and one to the Bias), and one neuron on the output layer corresponding to the output parameter.

Regarding the neurons on the hidden layer a series of configurations were examined to reduce the errors, arriving at a number of 18 neurons.

The training process was conducted at a rate of 0.56 and the number of epochs was originally established at 5000. The last adjustment for the synaptic weights occurred after 3548 epochs.

The chart for the targeted values and the modeled values of the specific heat loss and the error between them for 70 cases on which the neural network gets validated are shown in Figure 3. It can be seen an almost perfect overlap between the two graphs, which demonstrates the networks capability to determine the required value with sufficient accuracy.

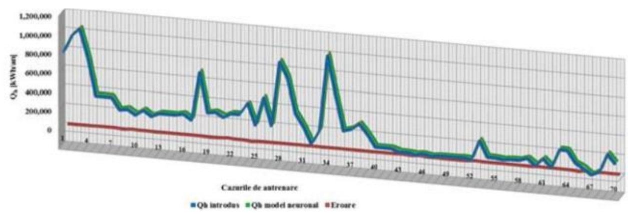

Figure 4: The chart for the targeted, the modeled values and the error for the ANN

Once trained for these cases, the neural network can predict the annual energy consumption for heating and electric for new cases, by modifying any of the input neurons values. The new values must not exceed the trained interval by a large amount; otherwise the possibility of error will increase.

6. Conclusions

The COVID-19 pandemic has been developing into one of the most severe challenges that the humankind has been facing in the long history.

Structural changes in energy demand and consumption have been observed in the (a) short-term versus long-term expectations, (b) different sectors of the energy industry, (c) residential versus non-residential consumptions, (d) peak demand patterns, (e) consumption philosophy during and after lockdowns, (f) consumed products, and (g) energy intensities in different regions.

The pandemic situation has been still developing, continuous observations and research are important to be conducted to provide as many benefits from this challenging development in the energy industry. Although COVID-19 caused many energy-related challenges, with learned lessons and proper actions, it offers opportunities and motivations to envisage and build a high energy-efficiency and low-carbon future.

The application of the neural network in order to determine the energy consumption in residential buildings can be done successfully due to their ability to overcome the problems of non-linearity between the input parameters and the values to be calculated. This method can be used for all kind of predictions in energy consumption areas, thermal and electric energy being the first to be experimented in this case. ANNS cand be used in fluctuating envoirements due to their ability to overcome the problems of non-linearity between the input parameters and the values to be calculated. So the decision to use computer and machine learning in order to predict energy consumptions is the most logical one.

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Rusu Daniel Sorin received his Phd. Diploma in Civil Engineering from Techincal University of Cluj-Napoca in 2012. Currently he is a lector at the Faculty of Building Services, specialized in Computer Aided Engineering. He is also a consultant and a designer in energy efficiency systems for residential and industrial sectors.