A Neural Network-based Methodology for Non-Intrusive Energy Audit of Telecom Sites

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Simone Eiraudo*, Luca Barbierato*, Roberta Giannantonio†, Edoardo Patti*, Lorenzo Bottaccioli* and Andrea Lanzini*
*Energy Center Lab, Politecnico di Torino, Turin, Italy. Email: name.surname@polito.it
†Data Office, TIM S.p.A., Italy, Email: name.surname@telecomitalia.it

***Abstract*—Energy Signatures (ES) are simple multi-purpose energy audit techniques. For instance, ES are employed in *i)* the determination of the Balance Point (BP) of a building, *ii)* the ranking of heating or cooling systems efficiency of a building, *iii)* the provision of building diagnostic information, and *iv)* the estimation of potential savings and strategies for more energy efficient buildings. In this paper, we propose an innovative energy audit tool based on a Neural Network (NN) for determining ES from aggregated electric load profile of industrial sites. The energy audit methodology defines and applies an innovative Key Performance Indicator (KPI), called Temperature Unstandardised Beta Weight (β^*_{Temp}), to take into account not only the thermal behaviour of the building, but also the cooling system efficiency and the electrical base load. This energy audit has been applied on a real-case electric consumption pattern dataset of around sixty Central Offices (CO) from a telecommunication (TLC) service provider in Italy. The useful outputs from the proposed methodology, together with its simplicity, effectiveness and applicability, are intended to support diffused understanding of buildings thermal behaviour with the perspective of enhancing energy efficiency and consumption reduction.**

***Index Terms*—Building Energy Efficiency, Energy Audit, Energy Signature, Neural Network**

I. Introduction

In recent years, building energy efficiency is among the most topical issues for energy research community [1]. Many obstacles complicate the pathway to a more environmentally sustainable way of consuming energy in buildings, such as the shortage of awareness over buildings energy behaviour and their inefficiencies. For instance, one of the most energy-intensive and inefficient load in buildings is cooling that represent nearly 16% of buildings final electricity demand in 2020 [2], not only for residential premises but also for commercial and industrial ones. Despite of the rise in cooling systems efficiencies and the building energy footprint reduction policies, this component of buildings' energy consumption has more than tripled over the last 30 years, and it grows relentlessly.

The way forward to enhance buildings behaviour awareness and identify their inefficiencies, such as for cooling loads, is providing practical tools for building analysis applications. Classic physical models are widely adopted for buildings performance assessment [3]. However, they necessarily require extensive information regarding the building structure, such as its thermal layout. Other approaches are data-driven ones that are becoming more and more popular and promise to cover a wider spectrum of building analyses. These approaches require lower computational and modelling effort and, in particular, they do not require information about the buildings' thermal layout. Even without this fundamental information, they may provide accurate results and enhance understanding and performance analysis of heating and cooling systems [4].

For instance, Energy Signature (ES) is a grey-box data-driven approach to point out the dependence of heating or cooling energy consumption from weather conditions [5]. The most simple case of ES is the univariate regression model that consider solely outdoor air temperature and energy consumption. Multivariate ES can be employed to analyse the impact of additional weather variables, such as solar radiation [6]. In the last decades, ES have been adopted to rank buildings heating systems efficiency, to produce diagnostic information, benchmarks, and control charts [7], and to calculate the Balance Point (BP) of buildings [8]. The latter represents the outdoor air temperature determining a thermal load equal to zero, that is the weather condition at which the building does not require heating nor cooling in order to keep indoor air temperature within a given range. In turn, computing a structure's BP provide crucial information about the building envelope and its thermal behaviour. For this reason, BP has been exploited by researchers to analyse the potential of ventilative cooling [9] and enhance accurate estimation of Degree-Day (DD) to support effective building-energy policy [10] and to predict HVAC systems energy consumption [11].

Most of the model-based approaches in literature to calculate BP result in challenging and time-consuming methodologies [7], [12]. For these reasons, in this paper we propose a novel energy audit methodology that exploits Feed-Forward Neural Network (NN) to accurately and automatically determine buildings ES from the aggregated load consumption profile. Unlike most of the works dealing with ES, our methodology allows usage of meter level electric consumption measurement instead of using the heating or cooling systems one, therefore avoiding intrusive installations of sensors for disaggregated loads metering. On the one hand, this represents an element of complexity in order to accurately determine a building ES. On the other hand, the non-intrusiveness of the proposed methodology represents a major advantage with the perspective of applying it to real case scenarios, as many buildings are not provided with adequate sensors for disaggregated load metering. Finally, this methodology applies a robust and simple model to estimate BP and cooling system performance by means of Temperature Unstandardised Beta Weight (β^*_{Temp}), a KPI which takes into account both Total Heat Loss Coefficient and the Coefficient of Performance (COP) of the cooling system. This work aspires to make novel contributions for what concerns both the employed tools for the ES analysis and the proposed energy KPI. Furthermore, this methodology will enhance *i)* the detection of inefficient sites, by means of comparative analysis of nearby and similar building, *ii)* the identification of abnormal power consumption, and *iii)* the estimation of best strategies for energy efficiency of industrial

buildings, that is providing retrofit scenarios.

In the following, Section II briefly presents the investigated research field, Section III describes the methodological pathway and the fundamental tools to be employed for the analysis, Section IV presents and discusses the outcomes of the appplication of the methodology to the case study. Finally, Section V contains the final remarks and outlines the future development of the study.

II. Case study and dataset

The contributions of the paper presented in the previous section were conceived to face the issues of a real-world dataset, containing the year aggregated load measurements with hourly resolution from around sixty Central Offices (CO) of the most important telecommunication (TLC) service provider in Italy. CO are industrial buildings housing the equipment devoted to the management of TLC networks.These buildings are characterised by an occasional and irrelevant presence of occupants. Most of the electrical demand is caused by the TLC equipment and to the huge electric demand of cooling systems to avoid overheating of the equipment itself. We will refer to these load contributions as P_{TLC} and P_{CLC} respectively. The minor load contribution from the auxiliaries and the lighting system is referred to as P_{Aux}, while P_{DISS} takes into account to energy conversion losses and the load due to the Uninterruptible power supply units [13]. TLC networks and their management buildings are rising dramatically their energy demands, featuring an annual increase of about 10% over the last decade [14].

III. Methodology

As it was presented in Section II, the investigated dataset contains aggregated electrical load data from a number of CO. In order to retrieve information about a building's thermal behaviour, the raw input data has to be properly preprocessed and analysed. The proposed methodology to handle these data is made of the following steps, as described by Figure 1: *i)* ***Data-Filtering***, *ii)* ***Re-sampling***, *iii)* electrical load ***Normalization***, *iv)* ***NN Training*** of a simple and ad-hoc designed NN and *v)* ***Energy Audit***, that includes achievement, visualisation and analysis of the results.

Data-Filtering: Data are filtered in order to remove possible unreliable data. These data may be caused by measurement errors or by anomalies in the electrical load pattern. This step enhances optimal training of the neural network and improves the accuracy of the energy audit. The task of detecting abnormal load values is carried out by means of a simple gradient-based statistical approach, which deletes single load values from time series whether they feature excessive gradient with respect to the previously recorder data.

Re-Sampling: The filtered dataset is then re-sampled to figure out each day mean electrical load. Indeed, it is well known that considering fine-grained load data may cause a drop in the accuracy of the energy audit, since transient phenomenon due to thermal inertia of the building cannot be described by the instantaneous response of the system.

Normalization: This step allows comparison among different buildings. This is crucial in order to achieve two of the goals of the proposed methodology, namely the comparative analysis and providing retro-fit scenarios. Indeed, awareness over a building energy efficiency shall be supported by

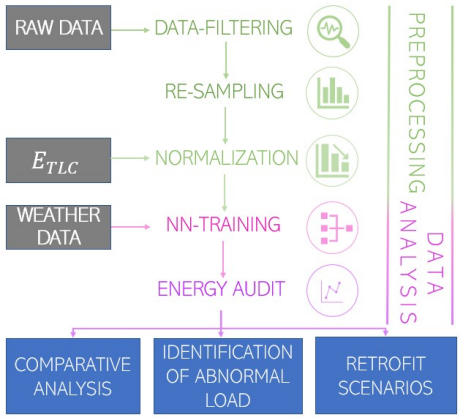

Fig. 1: Outlook of the proposed methodology

comparing its thermal behaviour to the one of nearby located and similar ones. In particular, we focused on pure CO, whose consumption is not affected by occupancy. Electrical load data are normalized with respect to the TLC equipment load. Indeed, these values somehow represent the buildings size. Furthermore, this is a fundamental step in order to retrieve information on the thermal behaviour of these buildings, as we will point out in Section III-A.

NN Training: A regression model shall be designed in order to assess the impact of outdoor weather variables on electrical load. Hence, outdoor air temperature is considered as input for a NN, while aggregated load is provided as an output and compared to real values. The dataset is split into training and validation subsets, which correspond to 2/3 and 1/3 of the dataset respectively, to ensure proper training of the network, that is avoiding under or over-fitting phenomena. The fundamental issue of the NN architecture is detailed in Section III-B.

Energy Audit: Finally, ES is obtained by the regression model retrieved by the NN, employing both the training and the validation set to achieve higher accuracy. The outcomes of the analysis are obtained and the typical parameters of buildings can be calculated. In particular, this methodology allows estimating the most important parameters describing the buildings' thermal behaviour and their efficiency of the cooling system. The following Section details these parameters and enlightens the physical issues underlying ES.

A. A Novel Approach to Energy Signature

Literature often refers to the coefficient k_{TOT} of the line obtained on an ES graph, displaying mean outdoor air temperature on the x-axis and mean cooling load on the y-axis, as thermal heat loss coefficient for what concerns heating ES, or as temperature sensitivity for cooling ES. Besides, ES usually refers to thermal load, being k_{TOT} measured in $\mathrm{kW_{Th}/°C}$ or $\mathrm{kW_{Th}/(°C * m^2)}$. Yet, in many cases measurements accounting for thermal power may not be available. On the other hand, since electricity represents the energy vector for the vast majority of cooling systems, the energy audit of a site may be obtained by considering electrical load. Furthermore, a non-intrusive approach shall support the wide-spread of the proposed diagnostic tool to any site whose total daily electrical demand is provided. This can be done by means of the following methodology. First, by making the assumption that the indoor air temperature within a CO is constant, that is that the building's shelter is

in thermal equilibrium with the outdoor environment [15], we can obtain the thermal balance:

$$\phi_T + \phi_V + \phi_{Sol} + \phi_{Cond} + \phi_{St} = 0 \tag{1}$$

where ϕ_T is the heat flux through the building envelope, ϕ_V accounts for the heat exchanged with the environment thanks to ventilation, ϕ_{Sol} is the heat gain determined by solar radiation, ϕ_{Cond} is the cooling power of the air conditioning system and ϕ_{St} is the internal heat generation. We assume that the latter contribution is equal to the electrical load by TLC devices, that is $\phi_{St} = P_{TLC}$. Then, we make the hypothesis that the heat gain determined by solar radiation has a negligible effect over thermal balance, that is $\phi_{Sol} = 0$. Furthermore, we consider the heat fluxes due to the cooling system, that are ϕ_{Cond} and ϕ_V, as a single contribution to thermal balance:

$$\phi_{CLC} = \phi_{Cond} + \phi_V \tag{2}$$

In addition, we consider the definition of temperature sensitivity and the well-known definition of COP:

$$\phi_T = k_{TOT} * (T_{ext} - T_{in}) \tag{3}$$

$$\phi_{CLC} = -P_{CLC} * COP \tag{4}$$

Considering equations from 1 to 4 and the aforementioned hypothesis, it may be easily found that:

$$P_{CLC} * COP = k_{TOT} * (T_{ext} - T_{in}) + P_{TLC} \tag{5}$$

It is worth pointing out that T_{in} formally represents the indoor air temperature. However, due to the constraints regarding control of indoor air temperature of CO and in accordance with the assumptions we made, this value is considered constant and can be regarded as Set Point Temperature T_{SP}.

According to what reported in Section I, if the outdoor air temperature is equal to the building's BP, the cooling systems is not needed to preserve T_{SP}. Hence:

$$k_{TOT} * (T_{BP} - T_{SP}) + P_{TLC} = 0 \tag{6}$$

Next, Equation 5 can be normalised by P_{TLC} and divided by the COP, obtaining:

$$\frac{P_{CLC}}{P_{TLC}} = \frac{k_{TOT} * (T_{ext} - T_{SetPoint})}{P_{TLC} * COP} + \frac{1}{COP} \tag{7}$$

Finally, considering Equations 6 and 7:

$$\frac{P_{CLC}}{P_{TLC}} = \frac{k_{TOT} * (T_{ext} - T_{BP})}{P_{TLC} * COP} \tag{8}$$

A crucial novelty proposed in this paper is to consider a new KPI, which we may refer to as Temperature Unstandardized Beta Weight (β^*_{Temp}). We define this KPI as the electrical load normalised rise with respect to TLC load per Celsius Degree, considering temperatures above the BP. This KPI measurements will hence be °C^{-1}. β^*_{Temp} takes into account not only the thermal behaviour of the building envelope, which is somehow described by k_{TOT}, but also the cooling system efficiency and the electrical base load (see Figure **??**). We define this KPI as:

$$\beta^*_{Temp} = \frac{k_{TOT}}{COP * P_{TLC}} \tag{9}$$

It should be also pointed out that calculating P_{TLC} is a trivial task. Indeed, the base load P_{base} of CO or Data Centers is generally considered as equal to the TLC equipment load P_{TLC} plus a contribution from power losses, namely P_{DISS}, which may be both assumed as constant values [13]. Furthermore, k_{TOT} is a constant value as well, being a characteristic parameter of the considered building envelope. The COP deserves more attention, since in some cases its value may have little variations depending on outdoor air temperature.

B. Design of Proper Tools for Energy Audit

Over the years, many researchers exploited iterative calculation methods for ES determination, as looking for the best-fit within a number of many possible linear regression models. For this reason, we provide an efficient quick, customizable and easy-to-use tool for determining BP and β^*_{Temp}. Indeed, we point out that a single hidden layer Feed-Forward NN may accurately find a rectified linear model representing ES of the site. The proposed network features the simplest type of element one may find in NN, namely the perceptron. This element may compute a simple operation as in Equation 10:

$$f(x) = \chi(\langle w, x \rangle + b) \tag{10}$$

where w is the weights vector, x is the inputs vector, b is the bias and χ is the activation function. The typical outlook of the employed NN is reported in Figure 2. This network may be fed with one or more external variables, that are outdoor weather variables, and provides total electrical load as output. Correlation analysis of the weather variables point out that temperature is the most relevant factor to determine electrical load in CO, as reported in Table I. These analysis clearly enlighten the minor relevance of the other weather variables, namely radiation, humidity and wind speed. This supports the hypothesis of negligibility of solar radiation made in the previous section. Hence, this is a case study investigating univariate ES, and the input layer will feature a unique node. It should be remarked that cooling load P_{CLC} is the only consumption quota which depends on outdoor temperature in a CO. Indeed, the other contributions, namely P_{Aux}, P_{DISS} and P_{TLC} are independent from weather factors. Hence, we may state that a total load variation determined by a temperature variation is a cooling load variation. This allow us to consider aggregated electrical load measurements, and supports the application of the proposed methodology to a number of sites. Nevertheless, employing total load instead of cooling load may cause the presence of noise in the regression models, with a slight impact on their accuracy.

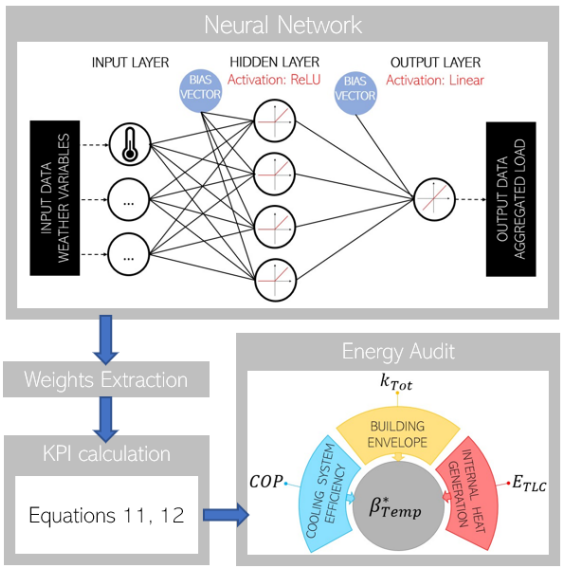

Fig. 2: The novel NN-based energy audit tool

Hence, one NN was trained for each CO, and the hyperparameters, specifically learning rate, learning rate decay and batch size, were tuned separately for each network by means of an automated grid search procedure. As we stated before, the ***input layer*** features, in this case, a single node. Hence, x vector's length will be one, specifically x will be x_{Temp}. Inputs data is normalized according both to minimum and maximum value, being scaled to the range 0-1. This is standard step for NN training.

The ***hidden layer*** represents the core of the NN. Linear ES may be easily obtained by setting a ReLU function as the activation one for this layer. In this way, each perceptron will provide an output equal to zero for any x such that:

$$w_{hidden,i} * x_{Temp} + b_i <= 0 \tag{11}$$

For instance, if we use a single perceptron hidden layer, the hidden layer will provide an output equal to zero for any temperature which does not determine any thermal load. From an energy point of view, these temperatures are all those ones below the so-called BP. Hence, this point may be easily found by turning the inequality reported in Equation 11 into its corresponding equation. On the other hand, models featuring multiple perceptrons in the hidden layer would be able to retrieve several elbow points. This means obtaining more than one cooling operating regime. In this case, the lower x_{elbow} represents the balance point.

Each cooling regime is characterised by its temperatures range and by the coefficient of the line in that region, that is β^*_{Temp}. These values can be obtained by:

$$\beta^*_{Temp,j} = \Sigma(w_{hidden,i} * w_{out,i}), \forall i | T_{BP,i} < T_{max,j} \tag{12}$$

where $\beta_{Temp,j}$ is the coefficient of the line in the cooling region j, $w_{hidden,i}$ is the weight of the incoming connection of perceptron i, $w_{out,i}$ is the weight of the connection among perceptron i and the perceptron in the output layer.

Finally, the ***output layer*** is made of a single perceptron which has to be configured with a linear activation function. This feature enhance the NN to determine the correct offset of the ES, that is the base load corresponding to the no-cooling region. This value, accordingly to the hypothesis reported in Section III-A corresponds to P_{TLC}, and can be simply retrieved by:

$$y_{base} = b_{out} \tag{13}$$

IV. Experimental Results

The proposed methodology was applied on a dataset of around sixty CO located in Italy. After preprocessing the raw data according to what reported in Section III, we carried out the data analysis. Hereafter, for sake of clarity, two significant case studies, whose ES are reported in Figure 3, are described and commented more in details. Hence, we initially focus on single-elbow points models. This is the case of estimating the existence of only two regions. The former corresponds to a no-cooling condition and is described by

TABLE I: Correlation Analysis within electrical load and weather variables from a CO

	P_{TOT}	T	RH	v_{wind}	G
P_{TOT}	1	0.884	-0.409	-0.230	0.376
T	0.884	1	-0.530	-0.286	0.484
RH	-0.409	-0.530	1	0.151	-0.522
v_{wind}	-0.230	-0.286	0.151	1	-0.157
G	0.376	0.484	-0.522	-0.157	1

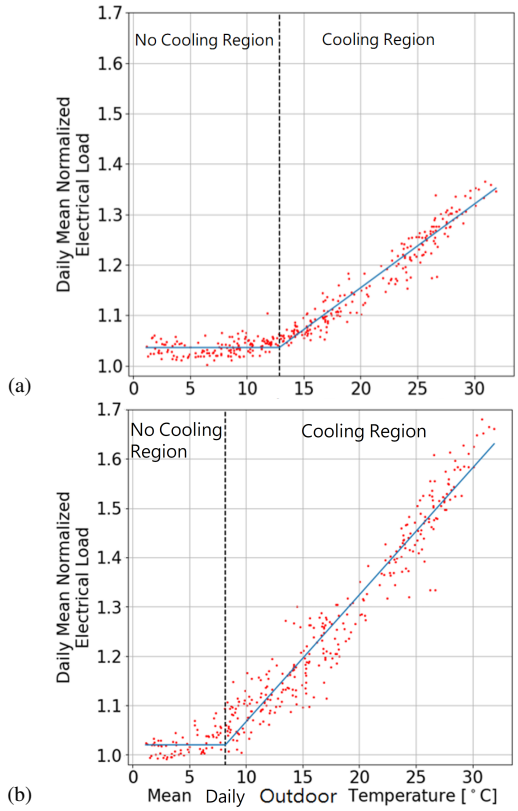

Fig. 3: Univariate ES obtained for two CO, employing single perceptron hidden layer NN

the flat part of the ES on the left sides of the two plots in Figure 3. On the other hand, the right part of the plots describes the buildings' electrical load as the cooling systems intervene. The increase of electrical demand due to outdoor air temperature rise is assumed to be constant and can be described by the coefficient β^*_{Temp}. The models designed achieved good performances for the whole dataset, as attested by the coefficient of determination R^2 values reported by the ES models from the buildings. Indeed, the mean R^2 value obtained was 0.827, while 50% of the models achieved values over 0.88 and 25% over 0.92. This confirms the consistency of the hypothesis reported in Section III, that is assuming that the electrical load of CO is firstly depending on outdoor air temperature. The proposed methodology performance slightly exceed the one from the most widely adopted SoA algorithm for ES, that is the iterative procedure to find the best fit to a two- segment linear regression [5], which achieved a mean R^2 equal to 0.822.

The two models in Figure 3 respectively reported R^2 values of 0.956 and 0.950. Still, accuracy of the model is the sole common trait within these two ES. Indeed, it may be easily seen that the cooling system of the building A, reported in Figure 3a, intervenes at 12.8°C, while the building B, in Figure 3b, features a much lower balance point, since it has to be cooled as soon as the outdoor air temperature reaches 8.2°C. Generally, the investigated buildings reported a T_{BP} mean value equal to 13.8°C. Less than 20% of the buildings reported a T_{BP} higher than 17 °C. Finally, a few COs are characterised by extremely low balance points, even below 10°C. To this extent, it should be remarked that CO may feature extremely dense internal heat generation. This means that cooling may be needed even if the indoor air temperature is much higher than the outdoor one. Notice that the indoor

air temperature is assumed to be equal to the set point, which, for the investigated COs, was set equal to 29°C by the energy managers to ensure equipment life [16]. By recalling Equation 6, it may pointed out that the BP is depending by T_{SP}, the internal heat generation and the thermal sensitivity of the building:

$$T_{BP} = T_{SP} - P_{TLC}/k_{TOT} \tag{14}$$

Since the T_{SP} is given and equal for any CO, the values of T_{BP} may be interpreted considering solely P_{TLC} and k_{TOT}. This issue of the thermal behaviour of CO may be easily understood by looking at Figure 4, reporting the experimental results retrieved for building A. This plot well enlightens 3 regions. Region A is the no-cooling region, which is characterised by thermal flux through the envelope toward the external environment capable of balancing the internal heat generation. As the outdoor temperature overcomes T_{BP}, we get into region B, as the cooling system intervenes in order to keep indoor air temperature below the set point. Nevertheless, heat transmission through the envelope still plays a role in removing heat from the building. The wider this region is, the higher potential savings can be achieved by means of a Free Cooling system [17]. The third region, reported as C in Figure 4, corresponds to the situation where the thermal flux through the envelope, ϕ_T, reverses, since the outdoor temperature is higher than the indoor, kept constant and equal to T_{SP}. In this case, the cooling system has to tackle with both the other contributions. Let us imagine to modify the building envelope to increase thermal flux through the walls, that is increasing k_{TOT}. ϕ_T, represented by the yellow line, would feature a steeper tilt. Since the T_{SP} is not modified, this would cause a rise in T_{BP}. This represents a first retrofit scenario. In this case, less energy would be wasted if the outdoor air temperature is below the T_{SP}. On the other hand, the electrical load would rapidly rise for hot days. Still, the building envelope and its internal heat generation are not the only factors affecting the electrical consumption caused by refrigeration of CO. Indeed, the thermal fluxes reported in Figure 4 do not take into account the efficiency of the cooling system itself. As we stated in Section III-A, the proposed KPI β^*_{Temp} is intended to describe this fundamental topic as well. The values retrieved by the methodology attest that a typical CO features β^*_{Temp} equal to $0.02759°\mathrm{C}^{-1}$. This means that the electrical demand for cooling increases of 2.76% per °C, for any temperature above T_{BP}. The β^*_{Temp} value represents the tilt of the line in the cooling region in the plots in Figure 3. It is worth remarking that the ES from building B enlightens,

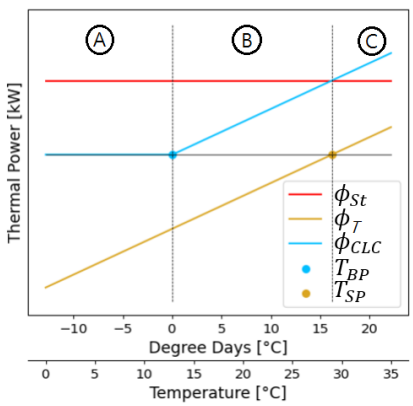

Fig. 4: Estimated thermal balance contributions in a CO

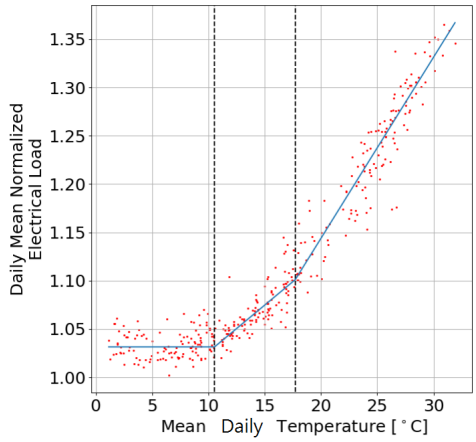

Fig. 5: A NN-derived ES featuring two elbow points

compared to building A, inefficiencies due to both a low T_{BP} and an high β^*_{Temp} value. Indeed, electrical demand features an electrical demand rise of $2.57\%°\mathrm{C}^{-1}$, compared to a rise of $1.66\%°\mathrm{C}^{-1}$ for building A. Finally, the cooling systems COP can be estimated. For instance, the buildings reported in Figure 3 have respectively COP equal to 3.72 and 1.87.

The easiness to modify the model configuration is one major advantage with respect to SoA algorithms. Indeed, the NN may be configured in order to identify more operating regimes. This can be done by setting multiple perceptrons in the NN hidden layer. The more perceptrons are included in the network, the higher will be the accuracy of the model. The results from the two-elbows configuration for building A are reported in Figure 5. The R^2 rises to 0.960, as the ES fits the load data more finely. In this case, two elbows are detected, at temperatures 10.7°C and 18.4°C. In this case, the former represents T_{BP}, while the second corresponds to a change in the cooling system operating regime. Indeed, while β^*_{Temp} is equal to $1.02\%°\mathrm{C}^{-1}$ for the first cooling region, the electrical load rise become more relevant in the right part of the ES, featuring a tilt of $1.91\%°\mathrm{C}^{-1}$. This phenomenon may be determined by the presence of multiple chillers, which intervenes at different temperatures. Any two-elbow ES we retrieved was characterised by an higher tilt on the second cooling region. This looks very reasonable, as if more than one chiller is available, the energy management would initially activate the more efficient one, while the second would intervene just in case the former is not capable of facing with the whole thermal load.

V. Conclusion and Future Work

A simple and effective NN-based tool was proposed to calculate ES by solely considering aggregated electrical load of industrial premises. This methodology shall support widespread of energy audit and enhance awareness over the energy behaviour and potential inefficiencies of not sensorized buildings. The methodology was tested on a real case dataset from an energy intensive industrial sector, namely the telecommunication one. The proposed model is characterised by good performance, achieving a mean R^2 equal to 0.827, and by a flexible configuration to explore different cooling operating regimes. Simple equations enhance extraction of fundamental information from the bias and connection weights of NN. In particular, balance point temperature, the novel KPI β^*_{Temp}, accounting for multiple aspects of buildings' thermal behaviour, and the cooling

system COP were calculated. The outcomes of this study shall be deepened, analysing typical retrofit scenarios, such using a Free Cooling system, improving efficiency of the cooling system or modifying the building envelope. Further work has to be done in order to validate the correct number of elbow points to be considered for estimating a building ES. Finally, higher accuracy of the models can be achieved by including additional weather variables in the regression model.

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REFERENCES

[1] Energy efficiency directive. (Accessed: May. 24 2021). [Online]. Available: https://ec.europa.eu/energy/topics/energy-efficiency/targets-directive-and-rules/energy-efficiency-directive_en

[2] Cooling. (Accessed: May. 25 2021). [Online]. Available: https://www.iea.org/reports/cooling

[3] I. Gaetani, P.-J. Hoes, and J. L. Hensen, "Estimating the influence of occupant behavior on building heating and cooling energy in one simulation run," *Applied Energy*, vol. 223, pp. 159–171, 2018.

[4] J. K. Hwang, G. Y. Yun, S. Lee, H. Seo, and M. Santamouris, "Using deep learning approaches with variable selection process to predict the energy performance of a heating and cooling system," *Renewable Energy*, vol. 149, pp. 1227–1245, 2020.

[5] F. Jacobsen, "Energy signature and energy monitoring in building energy management systems," in *Proceeding of CLIMA 2000 world congress*, vol. 3, Copenhagen, Denmark, 25-30 Aug. 1985, pp. 25–31.

[6] L. Tronchin, M. Manfren, and B. Nastasi, "Energy analytics for supporting built environment decarbonisation," *Energy Procedia*, vol. 157, pp. 1486–1493, 2019.

[7] R. Hitchin and I. Knight, "Daily energy consumption signatures and control charts for air-conditioned buildings," *Energy and Buildings*, vol. 112, pp. 101–109, 2016.

[8] A. Anjomshoaa and M. Salmanzadeh, "Estimation of the changeover times and degree-days balance point temperatures of a city using energy signatures," *Sustainable cities and society*, vol. 35, pp. 538–543, 2017.

[9] A. Belleri, M. Avantaggiato, T. Psomas, and P. Heiselberg, "Evaluation tool of climate potential for ventilative cooling," *International Journal of Ventilation*, vol. 17, no. 3, pp. 196–208, 2018.

[10] S. Park, J. Shim, and D. Song, "Issues in calculation of balance-point temperatures for heating degree-days for the development of building-energy policy," *Renewable and Sustainable Energy Reviews*, vol. 135, no. July 2020, p. 110211, 2021.

[11] H. Sha, P. Xu, C. Hu, Z. Li, Y. Chen, and Z. Chen, "A simplified hvac energy prediction method based on degree-day," *Sustainable Cities and Society*, vol. 51, p. 101698, 2019.

[12] G. Krese, Ž. Lampret, V. Butala, and M. Prek, "Determination of a building's balance point temperature as an energy characteristic," *Energy*, vol. 165, pp. 1034–1049, 2018.

[13] M. Sorrentino, M. Bruno, A. Trifirò, and G. Rizzo, "An innovative energy efficiency metric for data analytics and diagnostics in telecommunication applications," *Applied Energy*, vol. 242, no. March, pp. 1539–1548, 2019.

[14] S. Lambert, W. Van Heddeghem, W. Vereecken, B. Lannoo, D. Colle, and M. Pickavet, "Worldwide electricity consumption of communication networks," *Optics express*, vol. 20, no. 26, pp. B513–B524, 2012.

[15] A. Petraglia, A. Spagnuolo, C. Vetromile, A. D'Onofrio, and C. Lubritto, "Heat flows and energetic behavior of a telecommunication radio base station," *Energy*, vol. 89, pp. 75–83, 2015.

[16] D. Demetriou, "Effectively applying the expanded ashrae guidelines in your data center," *IBM Systems Report*, 2015.

[17] H. M. Daraghmeh and C. C. Wang, "A review of current status of free cooling in datacenters," *Applied Thermal Engineering*, vol. 114, pp. 1224–1239, 2017.