Application of Artificial Neutral Network and Geographic Information System to Evaluate Retrofit Potential in Public School Buildings

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ABSTRACT

School buildings in Italy are old, in critical maintenance conditions and they often perform below acceptable service levels. Nevertheless, data to guide renovation policies are missing or very expensive to retrieve. This paper presents a methodology for evaluating building’s energy savings potential, using the Certificazione Energetica degli Edifici (CENED) database, concerning energy performance labelling. Data are first clustered to identify most common thermo-physical properties. Three retrofit scenarios are then defined and energy savings potential, for each of the three, is evaluated through eight neural networks. Ultimately, data are geocoded and further processed to guide the definition of the retrofit strategy in most critical areas in Lombardy region. The results of the three scenarios proved that the highest energy savings can be obtained through retrofit interventions on around 50% of buildings. In conclusion, further insights on retrofit costs analysis and future development of the research are discussed.

KEYWORDS

Energy retrofit, school buildings, open data, ANN, GIS, data-driven process.

INTRODUCTION

School buildings in the Lombardy region, Italy, are obsolete and in critical maintenance conditions, therefore their performances are below acceptable service levels. Among unsatisfactory performances, those related to thermal comfort are extremely critical since they are strictly connected to the pupils’ learning ability [1] and to the (over)use of fossil fuels. Thus, under-performing buildings give rise to waste of public resources and pollution, contributing to climate change dynamics. Moreover, high costs for data gathering and analysis often force public administrations to make strategic decisions on the refurbishment of school buildings based on limited information. This is often a time and cost consuming process: approximatively one third of maintenance costs are used inefficiently as a result of improper and unnecessary maintenance activities.

The administration of the Lombardy region provides a public database of Energy Performance Certificates (EPC), called in Italian the *Certificazione Energetica degli Edifici* (CENED) database [2]. This database encompasses data about buildings energy performances (both primary energy and net energy), geometry (volume, gross and net surface, windows area, etc.) and technologies (mainly average thermal transmittance of building components and some information about plants' efficiency). These data can be used to drive the retrofit of school buildings, allowing better strategic decisions without increasing costs needed to acquire the knowledge about current energy performance of buildings.

Artificial Neural Networks to forecast energy demands

Building energy demands prediction is one of the most relevant topics for the definition of an effective asset management strategy. In the literature, three main approaches for addressing the issue can be spotted: the white-box approach corresponding to the engineering approach; the black box approach, namely the machine learning approach and the grey box approach, which can be intended as an hybrid solution between the former two [3–4]. Despite being all widely exploited, the black box approach allows to reach the objective of prediction in a faster and highly precise way, compared to the other two, especially when the dataset to be analysed is rather extended and complex [5]. ANN is a subset of machine learning. This method, whose behaviour is similar to the biological neural networks, allows to predict values with high accuracy against a low amount of input variables due to its ability to exploit a set of equations characterised by two functions: the "activation function" and the "transfer function". These functions trigger a sequence of connected nodes, namely the neurons of the ANN. Typically, the network is formed by an input layer of information to be processed, an output layer of values and a set of intermediate layers where the activation and transfer functions take place [6]. The number of intermediate layers can vary as well as the number of artificial neurons in each layer. The main advantage in the use of this tool concerns the possibility to forecast extremely reliable values using few input parameters.
Several studies have been carried out for energy prediction exploiting ANN: from the first studies concerning the prediction of utility loads forecasting in 1990s, until more recent researches on the energy saving potential of refurbished buildings [7].

Geographic Information Systems supporting strategic decisions

Geographic Information Systems (GIS) are software capable to handle a great amount of data, coupling quantitative and qualitative information with geographic one. These system have been exploited for the analysis of georeferenced data since 1960s when they have been employed by the Canadian Government for the implementation of the Canadian Land Inventory [8]. In Italy, and in particular in the Lombardy region, urban planning decisions at the municipal and regional level must be taken based on the support of geographic information compliant with directive INSPIRE [9], therefore according to an homogeneous and harmonised framework for information management [18]. Based on the above mentioned circumstances, GIS database for the Lombardy region is rather developed and rich [11] and can be considered as a fundamental resource for analysis and representation of phenomena at the regional level. Accordingly, when data on energy performances of buildings are georeferenced and handled through the GIS platforms, they can be combined with a huge amount of information coming from different databases and sources. Moreover, being traditionally considered a tool for strategic decision, it can be intended as the most suitable tool for synthesis and representation analysis and predictions carried out with the ANN process.

School buildings stock in Italy

From Italian Government's view point, energy efficiency is a key driver for improvement of school buildings. This stock amounts to 35% [12] of the entire national building stock and, most of the time, it requires deep refurbishment and maintenance interventions. Taking into account the whole national territory, 75% of school building dates before energy laws: 33% before Law 373/76 [13] and 25% before Law 10/91 [14]. Moreover, glancing at the current period, this stock must be compliant with more recent standards [15] and EU Directives [16]. School building stock counts 45,000 public schools out of 62,000, which overtake public housing sector with an energy consumption of approximatively 1 million Tonnes of Oil Equivalent (toe) per year (70% heating and 30% electricity). Accordingly, it is possible to optimise these energy consumption with remarkable improvements, not only with retrofitting interventions on buildings, but also by promoting energy behavioural awareness, for which the actual energy consumption is estimated to be reduced by 20% [17]. On the other hand, interventions on envelope and thermal plants can heavily reduce energy consumption and running costs, though they generate additional investment costs. 40% of school buildings need refurbishment intervention: it could be feasible to include the mark-up cost of energy consumption improvement in overall costs for buildings' refurbishment interventions. These interventions could decrease the actual average energy consumption of public schools (180 kWh/m^{2}year) towards those required for new constructions (30-40 kWh/m^{2}year) introduced by national regulations since 2009 [18].

Aims of the research work

Altogether, considering the state of the art and the scope of the research, it can be stated that ANN have been already employed for classification of consumption of buildings and labelling of buildings and that GIS are used in supporting policy making. Nevertheless, the combination of ANN and GIS for estimation of energy savings at the regional level has never been used to develop an energy policy. In the next section, the setup of a portfolio management strategy for school buildings energy retrofit is presented. The feasibility and the robustness of the strategy is enhanced based on the combined use of the tools described in the introduction.

METHOD

In this research, raw data coming from the CENED database have been processed to exclude inconsistent values. Then they have been clustered to acquire a good knowledge of the building stock and used to train some multi-layer feed-forward ANN that proved to be reliable instruments to forecast energy performance of school buildings [6–7]. Database cleaning is an operation with primary importance, because of the huge number of manifestly wrong data found: almost half of the energy labels in the database has been discarded.
School buildings have been analysed and classified according to their age (in an overall time span of more than one hundred years) and envelope's performances, defining some homogeneous classes of comparable school buildings. For each class some retrofit strategies, suitable with their characteristics, have been defined and the potential energy savings have been computed through the trained ANN. The output data have been imported in a GIS software, through which it has been possible to carry out a spatial analysis for the whole Regione Lombardia territory. The results of this analysis are presented, stressing the fact that a low-cost analysis can affect decisions on more than 1,500 school buildings.
Despite the existence of a gap between actual and computed performance and the imprecise predictions of the ANN, the proposed process balances the reliability of energy savings forecasts, with the necessity of decreasing efforts and expenses to carry out the estimation. Moreover, it allows to easily spot the most convenient retrofit strategy for the whole school building stock, even in the very early stage of the decision process.

Database cleaning

The first step of the work carried out on the dataset, concerns the database cleaning. This sequence of operations allowed to avoid massive errors in the following phases. CENED database (DB) comprehend a very extensive set of information concerning energy performances of buildings in Regione Lombardia. Therefore, the first operation that is accomplished concerns the selection of the only records related to schools. Then, not completed records have been deleted, since they do not completely describe the energy performance of the buildings. Once these two very first operations have been completed, the database has been further refined, according to the parameters listed in Table 1 [6].

Table 1. Constraints to spot unreliable labels in the CENED database

CENED database parameter	U.M.	Threshold
Heated gross surface	m^2	< 250
Heated gross volume / heated gross surface	m	< 2.5
Building envelope surface	m^2	< 5
Walls or Roofs thermal transmittance	W/m^2K	< 0.05 or > 17
Windows thermal transmittance	W/m^2K	< 0.1
EPh/ETh	-	< 0.5 or >1.5

Through the DB cleaning, almost 50% of the whole database has been removed. Form the initial record number of 2,915 rows representing only the school buildings, a reduced DB of 1,632 rows has been achieved.
The following phase of the research concerns a set of specific analyses carried out in order to acquire a deep knowledge of the database to be handled for energy consumption prediction of the school buildings. Buildings in the CENED DB are organised by construction year, as can be seen in Figure 1. The representation of the energy labels by construction year shows a peak for classes 1961-1976 and 1977-1992. If this trend is combined with information provided by the analysis in Figure 2, it is needless to say that the energy retrofit for these two classes is fundamental for the definition of an effective portfolio management strategy.

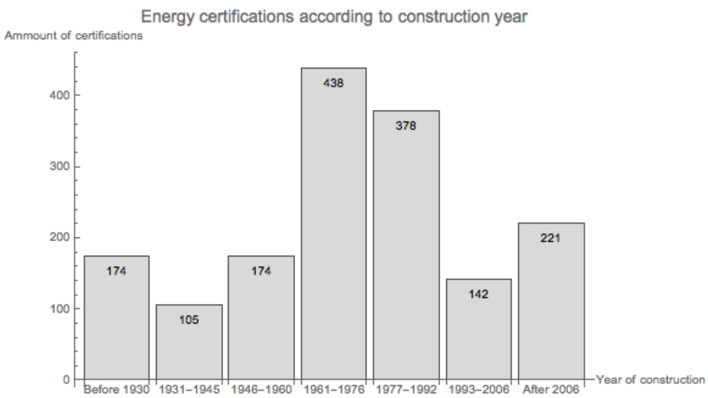

Figure 1. Labels groups according to the year of construction (7 groups)

Nevertheless, the most critical class concerns the schools built before 1930. This is rather easy to understand, since it is likely that those buildings, due to the typology of systems installed, the effects of time, the constant use of the facilities and the spaces and the inherent degradation of their components, show a low performance level, especially for what concerns the energy issues.

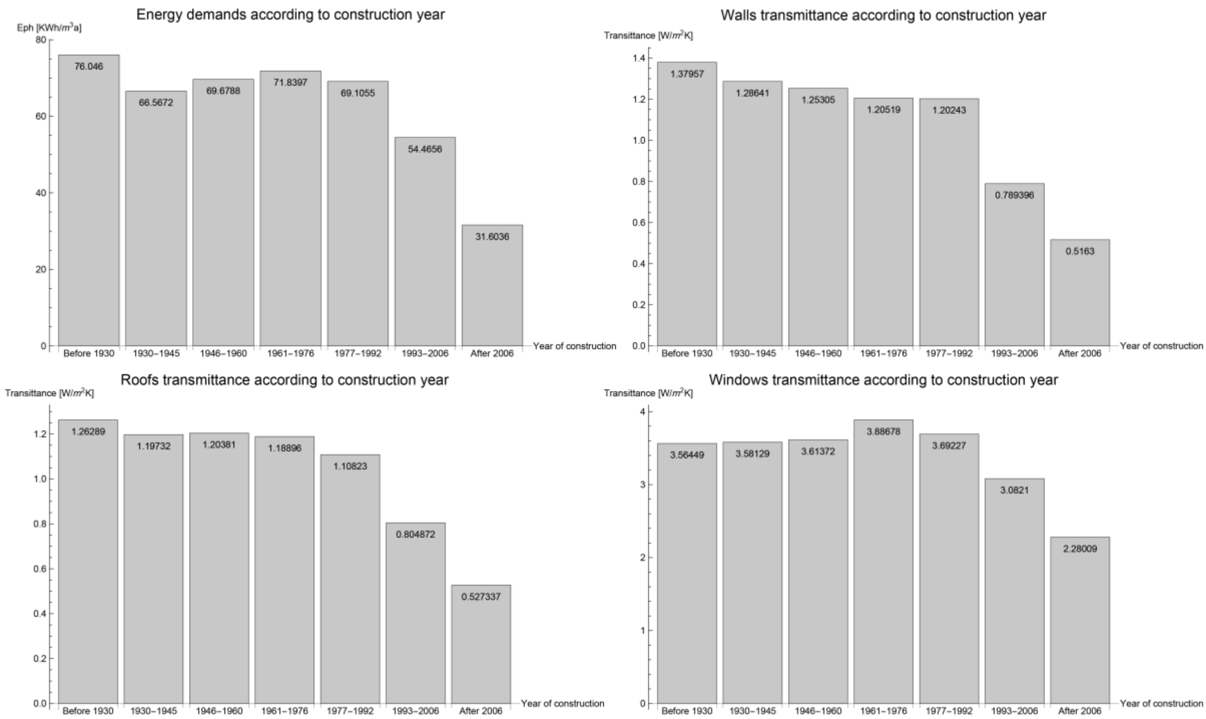

Figure 2. Main envelope characteristics and building EPh divided by class

Finally, Figure 3 represents the winter demand of primary energy consumptions (EPh) related to the thermal transmittance (U-value) of the three main technological unit of the envelope: windows, roof and walls.

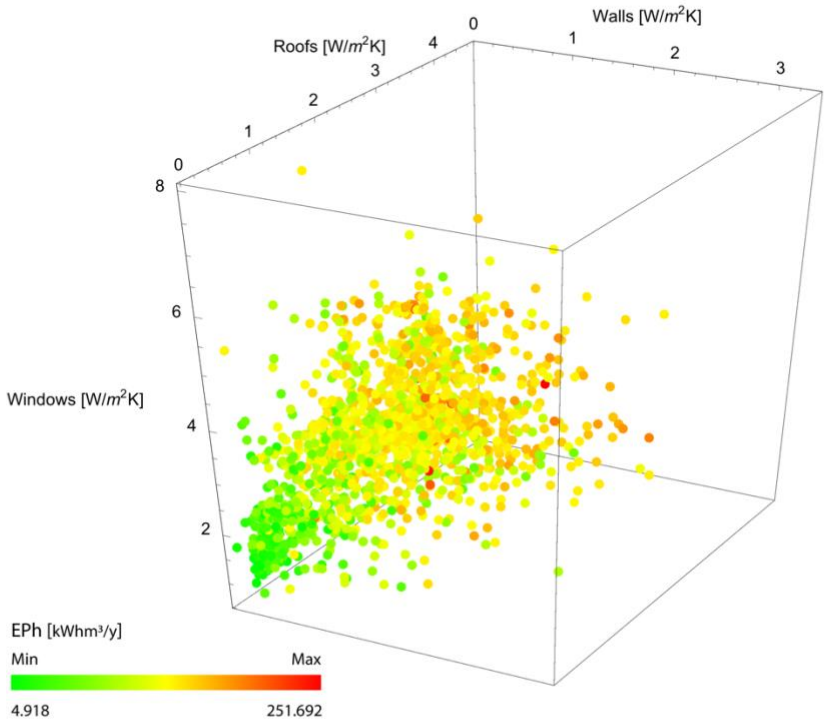

Figure 3. EPh according to thermal transmittance of walls, windows and roofs

Clustering building technologies

Further analyses have been carried out on the DB. For the definition of an appropriate retrofit strategy, it is necessary to identify homogeneous classes of building, on which to implement retrofit interventions. To do so, a clustering technique has been chosen and, for each of the three envelope's main technological units (walls, roofs and windows) a clustering algorithm has been run. This gave as output a clusterization of U-values almost always according to three groups. As an example, in Figure 4 are described clusters obtained for the technological unit walls over 4 classes of construction year. The U-value thresholds identified for the clusterization can change according to the sample taken into account, thus colours only represent the belonging to a specific cluster and not the width of the cluster.

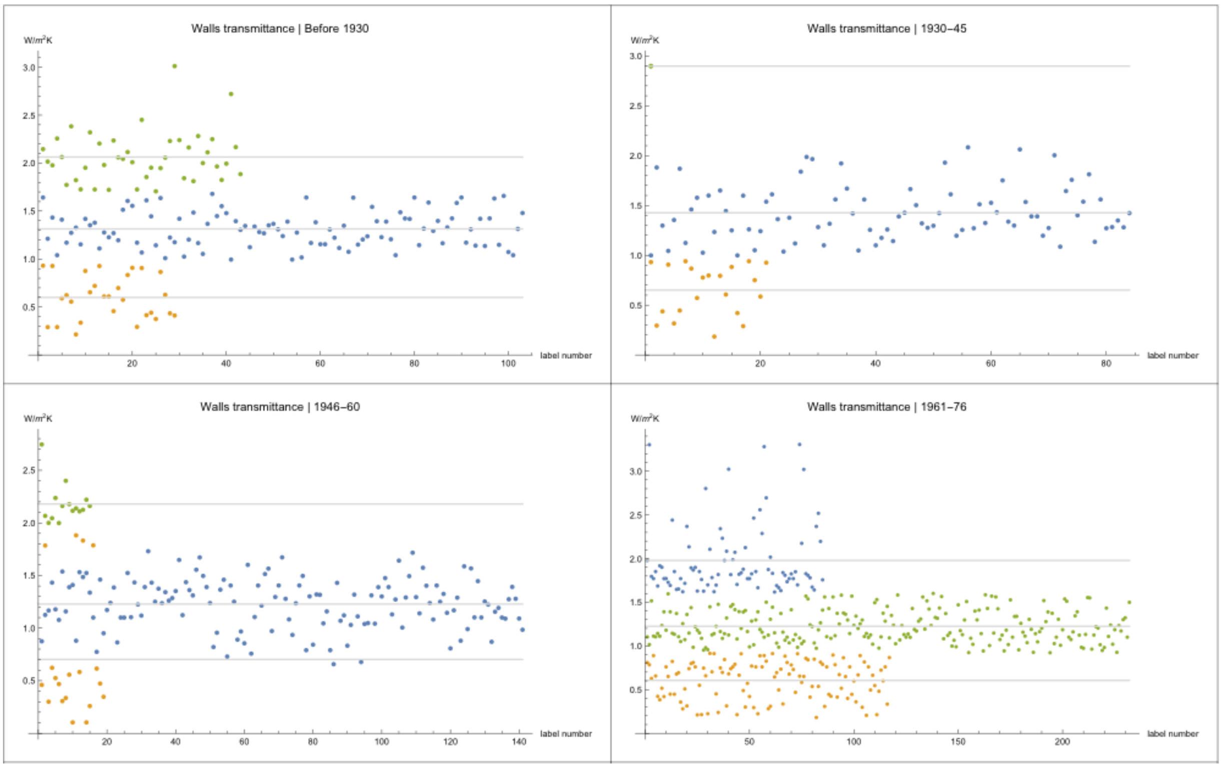

Figure 4. Clusters of walls' thermal transmittance according to construction year

Figure 4 provides only data concerning walls, since the representation of 21 clusterization analysis for the three main technological units would have been too long. The lower cluster, for all the components and classes of construction years is considered as the best performing situation, especially for those buildings belonging to the older construction year classes. Nevertheless, Table 2 shows the mean of each cluster for the three components of the school building envelope. As can be seen in Table 2, roofs are responsible for the largest energy flows, thus for the highest energy demands. These analysis, are the starting point for a further step of this research, concerning the identification of the most suitable technological solutions according to the construction period, and U-values and the related refurbishment costs. These analyses are not present in this article, since they are a further development.

Computing savings with Artificial Neural Networks

Once analysis employed for achieving the knowledge of the database have been carried out, the savings have been predicted by mean of the ANN. In the following paragraphs the steps for achieving these results are described.

Table 2. Mean U-values for each cluster and for the three components of the envelope

	Before 1930	1930-45	1946-60	1961-76	1977-92	1992-06	After 2006
	2.063	2.898	2.180	1.978	2.504		1.224
Walls	1.314	1.426	1.229	1.224	1.283	1.761	0.569
	0.600	0.651	0.702	0.606	0.666	0.731	0.273
	4.888	5.064		5.214	5.200	4.760	4.967
Windows	3.608	3.630	6.751	3.630	3.640	3.520	3.186
	2.211	2.152	3.596	2.097	2.257	2.346	1.736
	2.832		1.935	3.133	2.597		1.621
Roofs	1.518	1.274	1.397	1.524	1.528	1.463	0.679
	0.563	0.254	0.587	0.669	0.668	0.562	0.257

Artificial Neural Network training. CENED DB is divided in 7 timespans; therefore 7 ANN were trained on each CENED time span plus 1 trained on the whole cleaned CENED DB. The characteristics of the ANN are described as follows. The depth of the network (number of layers) and the type of each layer (type of equations implemented by the artificial neurons) have been chosen according to a trial-based process, which allowed to define the most suitable parameters. The number of neurons (in Table 3 the number below the type of function) of each layer has been optimized with an automatic process. Figure 5 shows the performance of the Total network, trained on the whole CENED dataset, according to the number of neurons on the layers. The ANN does not need input parameters directly related to the physical model in order to make reliable previsions. Therefore, input parameters have been defined empirically, as the ones that better interpolate the declared EPh values in the training phase. For instance, though the EPh takes into account also the building's systems, among the selected parameters the efficiency of the system is not considered. Parameters selected for the total ANN are:

1. winter degree days;
2. construction year;
3. gross surface [m^2];
4. gross volume [m^3];
5. dispersant surface [m^2];
6. ratio between glazing surface and dispersant surface;
7. ratio between opaque surface and dispersant surface;
8. average U-value of walls [W/m^2 K]
9. average U-value of roof [W/m^2 K]
10. average U-value of windows [W/m^2 K]
11. average U-value of basement [W/m^2 K].

For the other 7 ANN the selected parameters are the same, except for the construction year. In Table 3 are presented main characteristics of the ANN.
According to the layer of the ANN under analysis, functions employed are presented:

- Linear is the function characterising the layers with dense connections computing w.x+b;
- Tanh – net layer applies a unary function f to every element of the input tensor, in this case the function is the hyperbolic tangent;
- Ramp – net layer applies a unary function f to every element of the input tensor, in this case the function, gives x *if* $x \geq 0$ otherwise 0.

Table 3. ANNs characteristics

	<1930	1931-45	1946-60	1961-76	1977-92	1993-06	>2006	Total
Layer 1	Linear 9	Linear 9	Linear 9	Linear 9	Linear 9	Linear 9	Linear 9	Linear 10
Layer 2	Linear 126	Linear 406	Linear 196	Linear 412	Linear 158	Linear 68	Linear 236	Linear 476
Layer 3	Tanh 126	Tanh 406	Tanh 196	Tanh 412	Tanh 158	Tanh 68	Tanh 236	Tanh 476
Layer 4	Linear 126	Linear 406	Linear 196	Linear 412	Linear 158	Linear 68	Linear 236	Linear 476
Layer 5	Tanh 126	Tanh 406	Tanh 196	Tanh 412	Tanh 158	Tanh 68	Tanh 236	Tanh 476
Layer 6	Linear 63	Linear 203	Linear 98	Linear 206	Linear 79	Linear 34	Linear 118	Linear 238
Layer 7	Ramp 63	Ramp 203	Ramp 98	Ramp 206	Ramp 79	Ramp 34	Ramp 118	Ramp 238
Layer 8	Linear 1	Linear 1	Linear 1	Linear 1	Linear 1	Linear 1	Linear 1	Linear 1
Layer 9	Linear 1	Linear 1	Linear 1	Linear 1	Linear 1	Linear 1	Linear 1	Linear 1

The best forecasts are given by the mean of the prediction given by the ANN for the specific time span and of the one trained on the whole DB. In the case of Figure 6, the correlation between CENED data and predicted values is equal to 0.948329. This value is achieved combining the predictions of the single ANN per each class of year of construction with the prediction on the same values made by the ANN run on the total CENED database.

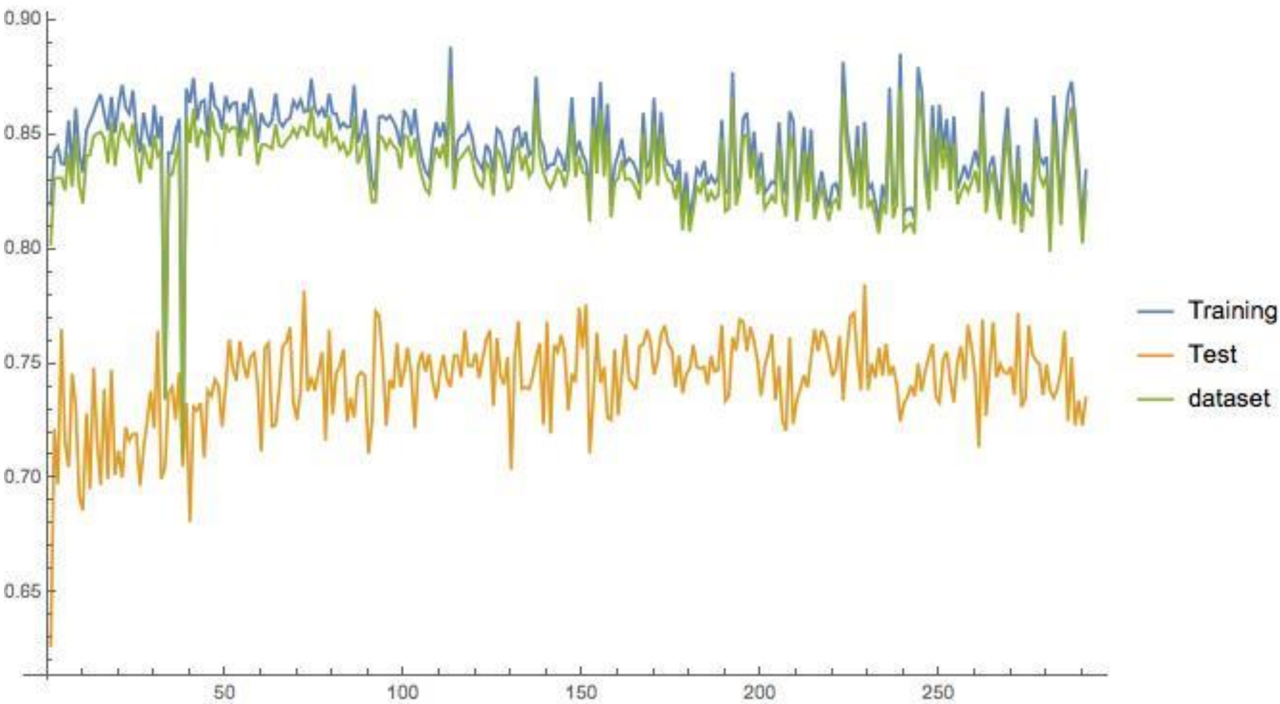

Figure 5. ANN performance according to the number of neurons (total dataset)

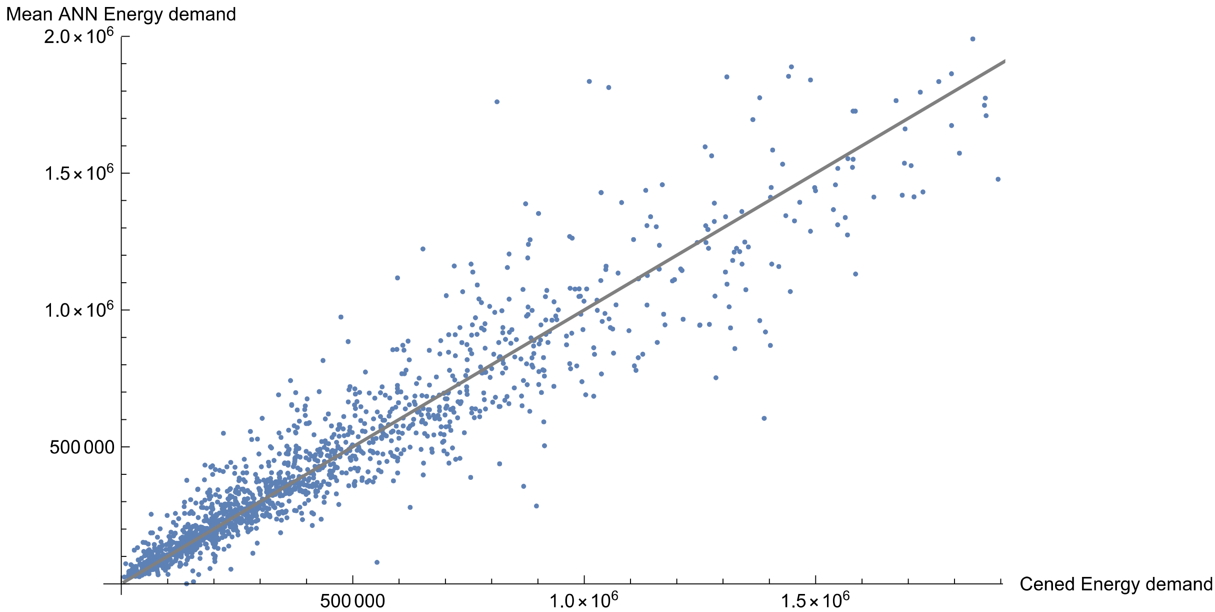

Figure 6. Correlation between the CENED Energy Demand and the one forecasted by the ANN

Use of Artificial Neural Networks to compute energy savings. Once the ANN have been defined and trained, they have been used for the prediction of energy savings, according to the three retrofit strategies described in Table 4. The parameters (U-values for Walls, roof and windows) have been chosen according to the clusterization process represented in Figure 4.

For the Case 1, U-values, respectively, for walls, roofs and windows equal to 1, 1, and 3.5 W/m^2K, represent the thresholds between the lower class and the intermediate class of the clusterization. Since the lower class is the best in terms of energy performances, the aim is not to retrofit school buildings already performing well, but to concentrate interventions on those which sit in a worst energy performance condition. Case 3, on the other hand, has been defined in order to be as effective as possible. Italian Decreto Ministeriale (DM) 26/06/2015 [19] defined for the Lombardy region limits of transmittance values for walls, roofs and windows sets to 0.26, 0.22 and 1.4 W/m^2K for buildings in climate zone E and to 0.24, 0.2 and 1.1 for buildings in climate zone F. The same thresholds have been adopted for ANN predictions in Case 3. Case 2 have been defined to spot an intermediate scenario between the two described above. Below are summarised key values for the three scenarios.

Although retrofit cases are described by parameters that do not consider the plants, ANNs have learned from a database where buildings with low levels of transmittance have efficient plants, thus prediction of energy savings already embed an improvement of the plants.

Table 4. Retrofit cases

	Case 1		Case 2		Case 3	
	U-value limit [W/m^2K]	Components below the limit	U-value limit [W/m^2K]	Components below the limit	U-value limit [W/m^2K]	Components below the limit
Walls	1	58%	0.5	82%	0.26/0.24	95%
Roofs	1	52%	0.5	78%	0.22/0.2	92%
Windows	3.5	49%	2	87%	1.4/1.1	97%

RESULTS

The energy savings are presented for each retrofit scenario, highlighting the total energy consumption pre-retrofit interventions, total energy consumption post-retrofit and total savings. Table 5,Table 6 andTable 7 present for each retrofitting typology, identified by main refurbished building components (Complete retrofit, Walls & Roof, Walls & Windows etc.) the number of retrofitted schools, total savings and average savings.

Case 1

Results obtained running the ANN are:

- total energy consumption in current circumstances (pre-retrofit interventions): $8.9712*10^8$ kWh/y;
- total energy consumption post-retrofit: $5.25874*10^8$ kWh/y;
- total savings $3.71246*10^8$ kWh/y, in average 227,200 kWh/y for each of 1,216 refurbished schools, out of 1,634 in the database.

Table 5: Number of retrofit schools, total and average savings by type of intervention (Case 1)

Type of retrofit	Complete retrofit	Walls & Roofs	Walls & Windows	Roofs & Windows	Only walls	Only Roofs	Only windows
Number of retrofit	462	227	153	68	98	88	120
Tot. savings [MWh/y]	185,228.92	57,387,267	53,250.59	25,433.07	9,107.18	8,153.68	19,392.92
Average savings [kWh/y]	400,928.40	252,807.34	348,043.07	374,015.67	92,930.41	92,655.45	161,607.68

Case 2

Results obtained running the ANN are:

- total energy consumption in current circumstances (pre-retrofit interventions): $8.9712*10^8$ kWh/y;
- total energy consumption post-retrofit: $4.19596*10^8$ kWh/y;
- total savings $4.77523*10^8$ kWh/y, in average 292,242. kWh/y for each of the 1,487 refurbished schools in the database, out of 1634.

Table 6. Number of retrofit schools, total and average savings by type of intervention (Case 2)

Type of retrofit	Complete retrofit	Walls & Roofs	Walls & Windows	Roofs & Windows	Only walls	Only Roofs	Only windows
Number of retrofit	1,166	38	118	56	19	14	76
Whole savings [MWh/y]	366,628.14	3,343.63	13,315.08	5,635.82	484.47	297.08	4,088.77
Average savings [kWh/y]	314,432.37	87,990.37	112,839.63	100,639.62	25,498.61	21,219.80	53,799.58

Case 3

Results obtained running the ANN are:

- total energy consumption in current circumstances (pre-retrofit interventions): $8.9712*10^8$ kWh/y;
- total energy consumption post-retrofit: $3.44654*10^8$ kWh/y;
- total savings $5.52466*10^8$ kWh/y, in average 338,106 kWh/y for 1,620 schools refurbished, out of 1,634.

Table 7. Number of retrofit schools, total and average savings by type of intervention (Case 3)

Type of retrofit	Complete retrofit	Walls & Roofs	Walls & Windows	Roofs & Windows	Only walls	Only Roofs	Only windows
Number of retrofit	1,497	20	25	36	4	12	26
Whole savings [MWh/y]	390,862.86	948.02	751.22	808.34	80.60	603.90	664.68
Average savings [kWh/y]	261,097.43	47,400.81	30,048.61	22,453.93	20,151.04	50,324.96	25,564.48

Figure 7 shows a comparison between the scenarios and the average savings per school. The graph confirms that increasing the number of buildings to be refurbished, decreases the average savings. This trend is due to the fact that lowering the thresholds of retrofitting parameters (walls, roof and windows transmittance), the ANN produces more complete retrofit forecasts than in the other two cases. The Case 1 can be considered as the most viable among the three, presenting higher average post-retrofit savings, though the percentage of total retrofit is much lower than in Case 2 and Case 3. This circumstance suggests that the average retrofit cost will be the lowest among the three cases. Despite the ANN having an extremely high precision, it must be taken into account that the database on which savings have been calculated is the cleaned one, therefore, some school buildings might not be present.

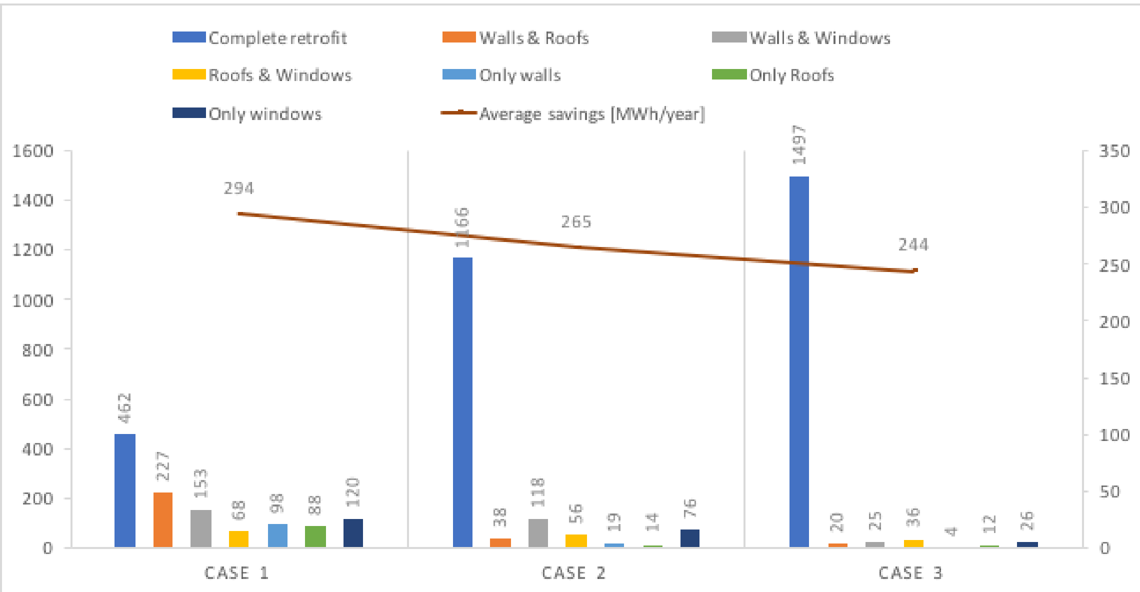

Figure 7. Number of retrofit works divided by type compared to the potential average savings

GOGRAPHIC INFORMATION SYSTEM INTEGRATION FOR PORTFOLIO MANAGEMENT

Results of the previous phases have been imported and processed in GIS. It is important to highlight that for synthesis reason, GIS analysis and representations are here presented only for one of the three retrofit scenarios. In order to integrate energy savings computed with the ANNs with spatial information it has been necessary to run a geocoding script. The address field in the CENED cleaned DB has been corrected according to the format required by the Google API, since the geocoding process has been carried out exploiting the online open geocoding service provided by Google. The geocoding process, gave as outcome a point layer, whose attribute table contain values processed through the previous data handling steps. The geocoding process gave an error log of 47 addresses not found, corresponding to 2.9% of the whole cleaned database. Points have been categorised and represented according to the predicted energy demands (dimension of the marker) and according to the type of intervention for achieving the energy retrofitting strategy (colour of the marker). Figure 8 only represents the school buildings retrofitted according to the Case 1.
The geographic representation of data obtained through ANN prediction allows to spot most critical areas in the Lombardy region, namely where through the retrofitting interventions it is possible to achieve the highest energy saving. These data, combined with other concerning, for instance, cost for retrofit interventions, age of the assets etc. can be exploited by the public administrations for making informed decisions.

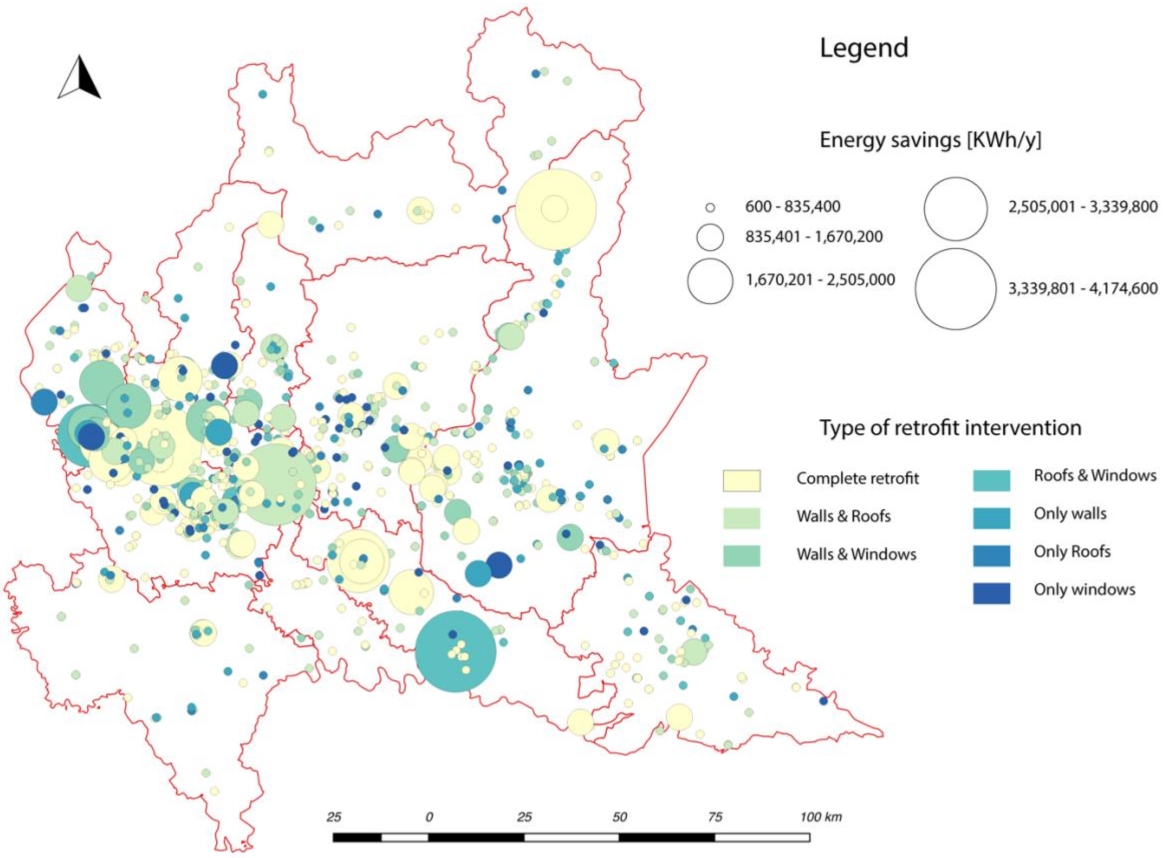

Figure 8. Energy savings computed through ANN by type of intervention in the Lombardy region.

DISCUSSION AND CONCLUSIONS

Regional administration needs inexpensive methods to find the way to address energy related issues and this research proved that the integrated use of open-data, ANN and GIS satisfies this need. The primary advantage of the proposed approach concerns the possibility to compute buildings' post-retrofit EPh without even inspecting them and using parameters which are easily found or computed. The second important outcome of the research is that it has demonstrated the feasibility and usefulness of using GIS tools in energy policies. Focusing on the case study, a third result of the research is that it is demonstrated that increasing the number of retrofitted buildings (selecting a lower U-value retrofit threshold for the envelope), average energy savings decrease. This suggests that the retrofit of the whole school buildings stock in Lombardy region is not cost-effective. Although energy savings are rather important for the development of an effective asset and portfolio management strategy, when dealing with school buildings, other parameters related to the learning performance should be taken into account. In order to prioritise retrofitting interventions, it is relevant, for instance, to take into account also compliance of the building to the contemporary standards (e.g. flexibility of the spaces, dimensions of the classrooms, fire safety codes etc.). Thus, the proposed methodology should be encompassed in a wider framework for decision making. A further development of the research concerns the identifications of the costs related to the retrofit interventions, this will be done through the identification of walling, roofing and glazing technologies according to the year of construction and the thermal transmittance. This requires further efforts in research and testing of the model. Moreover, despite the research has been carried out at the Lombardy region level, it is possible to apply the same steps for data processing to further datasets at the national or European level, since member states must be compliant to Energy Performance Building Directive (EPBD) [16].

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