Buildings Energy Prediction Using Artificial Neural Networks

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Abstract: This paper aims to prove that the artificial neural network (ANN) is a powerful tool in prediction of buildings energy consumption, this target is achieved by comparing the accuracy of ANN prediction with the output of simple linear regression algorithm and previous work. First of all, the flowchart depends on four main steps: 1) Data selection, 2) Data preparation, 3) Model training and tuning, and 4) Evaluate results. The Commercial Buildings Energy Consumption Survey (CBECS) is selected as a data set to apply ANN on it by choosing the most effective features that have the main influence on the energy consumption. Data preparation process is done by replacing missing values and outliers' values with median value of each feature. The model's hyper-parameters are tuned by manual method depending on the author expeience of ANN algorithm and the evaluation step done by using mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and r-squared value as a metric for performance. The results showed that the proposed ANN algorithm achives high performance comparing to simple linear regression algorithm and previous work on the same data.

1. Introduction

ANNs are the modeling of the human brain with the simplest definition and building blocks are neurons. Each ANN consists of multilayers of neurons. A standard ANN architecture as shown in figure 1 consists of input, output, and hidden layers. The input layer takes all the input values while the output layer generates the final result [1]. The disappearance of a few pieces of information in one place does not restrict the network from functioning. After ANN training, the data may produce output even with incomplete information. ANNs have successfully used for modelling non-linear problems and complex systems [2].When ANN gives a probing solution, it does not give a clue as to why and how. This reduces trust in the network. In addition to, there is no specific rule for determining the best structure of ANN. The appropriate network structure is achieved through experience and tune different structures using trial and error to achieve best performance [3-7].

ANNs is a powerful tool for modelling building energy modelling and reliable prediction. However, they require an accurate choice of network structure and precise tuning of its several hyper-parameters for training. The performance of the models is not guaranteed as ANN suffer from a local minimum problem where the solution not the best one. In addition, ANN should be fed with adequate number of samples in order to achieve acceptable accuracy. Otherwise it might be outperformed with simple MLR models. So ANN is much appropriate for engineers having a strong knowledge of deep learning and statistical modelling [3-5, 8]. The target of this paper, prove ability of using ANN algorithms in buildings energy field instead of simple linear regression algorithm and support this target by comparing results with two previous work on the same data to explain the required steps of getting high performance in prediction for energy consumption.

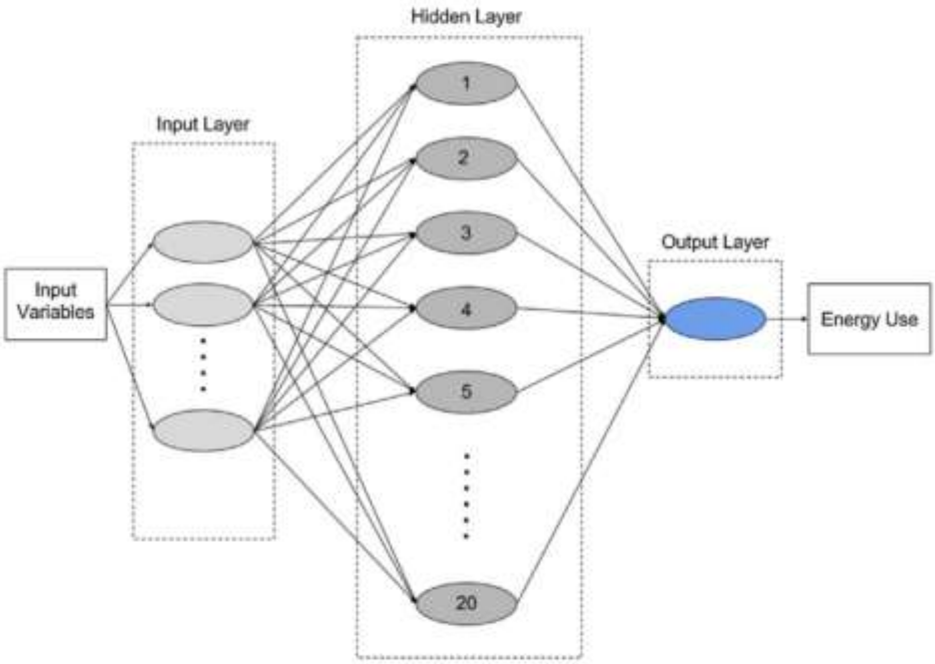

Figure 1: Artificial neural network (ANN) structure [1].

The first step to form a hidden layer is to construct hidden features based on linear combinations of the input data with next equation 1:

$$f(x) = (W * x) + b \qquad (1)$$

where W represents the weight and b represents the bias for each neuron. Each neuron would then require a nonlinear activation function and the identity function has been used for regression purposes. The outputs of hidden layers are then used as the inputs to the output function which generates the final regression result (prediction value) [1].

In this paper, to evaluate the deviation between the predicted and actual energy use, four terms are used: 1) Mean absolute error (MAE), 2) Mean square error (MSE), 3)

Root mean square error (RMSE), and 4) R-squared value. Equations are explained from 2 to 5, where n is the number of points in the CBECS data.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=0}^{n} |\text{true value} - \text{predicted value}| \qquad (2)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=0}^{n} (\text{true value} - \text{predicted value})^2 \qquad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=0}^{n}(\text{true value}-\text{predicted value})^2}{n}} \qquad (4)$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=0}^{n}(\text{true value}-\text{predicted value})^2}{\sum_{i=0}^{n}(\text{true value}-\text{average value})^2} \qquad (5)$$

2. Methodology

This section represents the steps that needed to make energy prediction in building field by applying the flowchart (Figure 2) on the Commercial Buildings Energy Consumption Survey (CBECS).

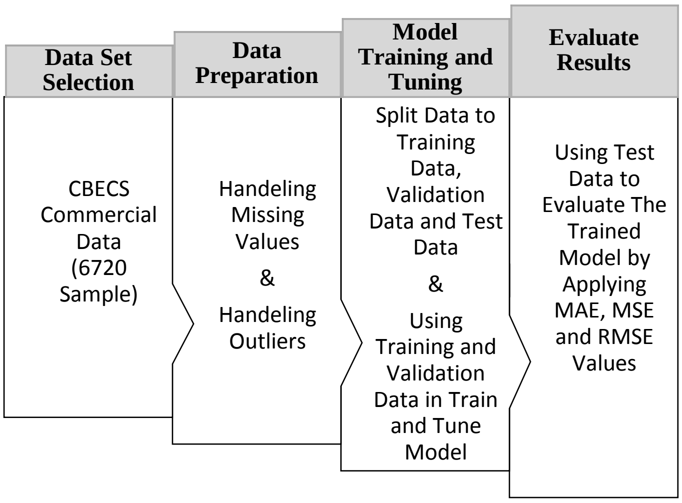

Figure 2: Artificial neural network flowchart to make building energy prediction [9, 10].

2.1 Data Set Selection Step

CBECS is an open source data set contain information on the stock of U.S. commercial buildings with size of 6720 building. CBECS includes building types such as schools, hospitals, correctional institutions, and buildings used for religious worship, in addition to traditional commercial buildings such as stores, restaurants, warehouses, and office buildings. In the Commercial Buildings Energy Consumption Survey (CBECS), buildings are classified according to principal activity, which is the primary business, commerce, or function carried on within each building [11, 12].

2.2 Data Set Preparation Steps

After choosing suitable data set to test the artificial neural network algorithm, data preprocessing step comes here. The numerical features are selected in addition to the main categorical features that effect on energy consumption in direct way or indirect way. The target during analysis is checking missing values, outlier values and understanding the nature of each feature distribution. The selected features are shown in (Table 1 and Table 2) which can be classified as: 1) Categorical features, and 2) Numerical features.

The categorical features are converted directly to one hot encoder after get rid of outliers and missing values in it. But in case of numerical features the preprocessing step need for calculation of mean and median for each feature (Table 2) to show the difference between mean and median that represent the effect of outliers on data distribution, in addition to calculate the percentage of missing values in each feature to identify how to deal with it. The change of the difference value represents the effect of outliers; the more outliers effect increases the more difference between mean and median increase. The visualization of missing values of each feature is very important to take a decision of which feature is suitable to taken in training neural network, because features with high percentage of missing values can't be taken.

Table 1: categories, percentage of each category of total data and percentage of missing values for each categorical feature

	Variable name	**Label**	**Categories Numbers**	**Percentage of Each Category of Total Data** (sorted from lowest to highest value)	**Percentage of Missing Values**
١	CENDIV	Census division (Categorical Feature)	'1' = 'New England' '2' = 'Middle Atlantic' '3' = 'East North Central' '4' = 'West North Central' '5' = 'South Atlantic' '6' = 'East South Central' '7' = 'West South Central' '8' = 'Mountain' '9' = 'Pacific'	New England = 4.75 East South Central = 5.83 Mountain = 6.70 West North Central = 8.32 Middle Atlantic = 11.71 West South Central = 12.68 East North Central = 13.39 Pacific = 16.56 South Atlantic = 20.06	0.00
٢	PBA	Principal building activity (Categorical Feature)	'01' = 'Vacant' '02' = 'Office' '04' = 'Laboratory' '05' = 'Non-refrigerated warehouse' '06' = 'Food sales' '07' = 'Public order and safety' '08' = 'Outpatient health care' '11' = 'Refrigerated warehouse' '12' = 'Religious worship' '13' = 'Public assembly' '14' = 'Education' '15' = 'Food service' '16' = 'Inpatient health care' '17' = 'Nursing' '18' = 'Lodging' '23' = 'Strip shopping mall' '24' = 'Enclosed mall' '25' = 'Retail other than mall' '26' = 'Service' '27' = 'Other'	Refrigerated warehouse = 0.31 Enclosed mall = 0.51 Laboratory = 0.61 Other = 1.29 Nursing = 1.40 Public order and safety = 1.50 Food sales = 1.92 Outpatient health care = 2.93 Vacant = 3.68 Lodging = 4.39 Strip shopping mall = 4.40 Religious worship = 5.24 Food service = 5.37 Retail other than mall = 5.49 Inpatient health care = 6.09 Public assembly = 6.16 Service = 6.31 Non-refrigerated warehouse = 10.98 Education = 11.24 Office = 20.18	0.00
٣	WLCNS	Wall construction	'1' = 'Brick, stone, or stucco' '2' = 'Pre-cast concrete panels'	Decorative or construction glass = 0.31 No one major type = 0.61	0.00

		material (Categorical Feature)	'3' = 'Concrete block or poured concrete (above grade)' '4' = 'Aluminum, asbestos, plastic, or wood materials (siding, shingles, tiles, or shakes)' '5' = 'Sheet metal panels' '6' = 'Window or vision glass (glass that can be seen through)' '7' = 'Decorative or construction glass' '8' = 'No one major type' '9' = 'Other'	Other = 0.62 Window or vision glass (glass that can be seen through) = 1.53 Pre-cast concrete panels = 8.54 Aluminum, asbestos, plastic, or wood materials (siding, shingles, tiles, or shakes) = 9.48 Sheet metal panels = 9.93 Concrete block or poured concrete (above grade) = 21.80 Brick, stone, or stucco = 47.17	
٤	BLDSHP	Building shape (Categorical Feature)	'01' = 'Square' '02' = 'Wide rectangle' '03' = 'Narrow rectangle' '04' = 'Rectangle or square with an interior courtyard' '05' = '"H" shaped' '06' = '"U" shaped' '07' = '"E" shaped' '08' = '"T" shaped' '09' = '"L" shaped' '10' = '"+" or cross shaped' '11' = 'Other shape'	"E" shaped = 0.97 "H" shaped = 1.72 "+" or cross shaped = 1.74 "T" shaped = 2.03 "U" shaped = 2.24 Rectangle or square with an interior courtyard = 3.72 "L" shaped = 6.06 Other shape = 6.13 Narrow rectangle = 7.27 Square = 7.91 Wide rectangle = 60.22	9.14
٥	MONCON	Month ready for occupancy (Categorical Feature)	'01' = 'January' '02' = 'February' '03' = 'March' '04' = 'April' '05' = 'May' '06' = 'June' '07' = 'July' '08' = 'August' '09' = 'September' '10' = 'October' '11' = 'November' '12' = 'December' '00' = 'Undetermined'	February = 1.72 January = 3.45 June = 3.45 September = 5.17 November = 5.17 July = 6.90 March = 6.90 August = 8.62 April = 10.34 October = 10.34 May = 10.34 Undetermined = 12.07 December = 15.52	99.14
٦	ACT1	First activity in building (Categorical Feature)	'11' = 'Office/Professional' '12' = 'Data center/Computer "server farm"' '13' = 'Warehouse/Storage' '14' = 'Food sales or service' '15' = 'Enclosed mall' '16' = 'Retail (other than mall)' '17' = 'Education' '18' = 'Religious worship' '19' = 'Public assembly' '20' = 'Health care' '21' = 'Service' '22' = 'Lodging' '23' = 'Public order and safety' '24' = 'Residential' '25' = 'Industrial' '26' = 'Agricultural' '27' = 'Vacant' '28' = 'Other'	Industrial = 0.27 Other = 0.27 Lodging = 0.27 Residential = 0.27 Religious worship = 0.53 Public assembly = 0.53 Service = 0.80 Health care = 1.06 Retail (other than mall) = 4.24 Education = 6.63 Food sales or service = 8.49 Warehouse/Storage = 11.41 Office/Professional = 65.25	94.39
٧	ACT2	Second activity in building (Categorical Feature)		Public order and safety = 1.86 Industrial = 2.65 Vacant = 2.92 Lodging = 2.92 Residential = 4.77 Religious worship = 5.04 Service = 6.10 Health care = 6.10 Other = 6.90 Food sales or service = 7.69 Education = 7.69 Public assembly = 10.08	94.39

				Retail (other than mall) = 11.94 Warehouse/Storage = 23.34	
٨	ACT3	Third activity in building (Categorical Feature)		Food sales or service = 1.16 Lodging = 2.33 Education = 2.33 Religious worship = 3.49 Public order and safety = 3.49 Health care = 6.40 Vacant = 6.40 Residential = 7.56 Retail (other than mall) = 8.72 Industrial = 12.79 Other = 13.37 Public assembly = 14.53 Service = 17.44	97.44
٩	PBAPLUS	More specific building activity (Categorical Feature)	'01' = 'Vacant' '02' = 'Administrative/professional office' '03' = 'Bank/other financial' '04' = 'Government office' '05' = 'Medical office (non-diagnostic)' '06' = 'Mixed-use office' '07' = 'Other office' '08' = 'Laboratory' '09' = 'Distribution/shipping center' '10' = 'Non-refrigerated warehouse' '11' = 'Self-storage' '12' = 'Convenience store' '13' = 'Convenience store with gas station' '14' = 'Grocery store/food market' '15' = 'Other food sales' '16' = 'Fire station/police station' '17' = 'Other public order and safety' '18' = 'Medical office (diagnostic)' '19' = 'Clinic/other outpatient health' '20' = 'Refrigerated warehouse' '21' = 'Religious worship' '22' = 'Entertainment/culture' '23' = 'Library' '24' = 'Recreation' '25' = 'Social/meeting' '26' = 'Other public assembly' '27' = 'College/university' '28' = 'Elementary/middle school' '29' = 'High school' '30' = 'Preschool/daycare' '31' = 'Other classroom education' '32' = 'Fast food' '33' = 'Restaurant/cafeteria' '34' = 'Other food service' '35' = 'Hospital/inpatient health' '36' = 'Nursing home/assisted living' '37' = 'Dormitory/fraternity/sorority' '38' = 'Hotel' '39' = 'Motel or inn' '40' = 'Other lodging' '41' = 'Vehicle dealership/showroom'	Other food sales = 0.03 Refrigerated warehouse = 0.31 Other public order and safety = 0.33 Courthouse/probation office = 0.39 Post office/postal center = 0.39 Other lodging = 0.40 Other food service = 0.40 Convenience store with gas station = 0.48 Vehicle dealership/showroom = 0.51 Enclosed mall = 0.51 Library = 0.55 Other retail = 0.61 Laboratory = 0.61 Medical office (non-diagnostic) = 0.62 Convenience store = 0.70 Grocery store/food market = 0.71 Dormitory/fraternity/sorority = 0.71 Preschool/daycare = 0.74 Other office = 0.77 Fire station/police station = 0.79 Repair shop = 0.79 Bar/pub/lounge = 0.89 Motel or inn = 0.91 Medical office (diagnostic) = 0.92 Other classroom education = 0.92 Other public assembly = 0.94 Bank/other financial = 1.18 Self-storage = 1.21 Other service = 1.24 Other = 1.29 Entertainment/culture = 1.32 Fast food = 1.40 Nursing home/assisted living = 1.40 Social/meeting = 1.46 College/university = 1.55 Vehicle storage/maintenance = 1.68 Recreation = 1.89 Clinic/other outpatient health = 2.01 High school = 2.11 Vehicle service/repair shop = 2.22 Hotel = 2.37 Restaurant/cafeteria = 2.68 Government office = 3.05	0.00

			'42' = 'Retail store' '43' = 'Other retail' '44' = 'Post office/postal center' '45' = 'Repair shop' '46' = 'Vehicle service/repair shop' '47' = 'Vehicle storage/maintenance' '48' = 'Other service' '49' = 'Other' '50' = 'Strip shopping mall' '51' = 'Enclosed mall' '52' = 'Courthouse/probation office' '53' = 'Bar/pub/lounge'	Mixed-use office = 3.15 Vacant = 3.68 Retail store = 4.38 Strip shopping mall = 4.40 Distribution/shipping center = 4.57 Non-refrigerated warehouse =.21 Religious worship = 5.24 Elementary/middle school = 5.91 Hospital/inpatient health = 6.09 Administrative/professional office = 11.40	
١٠	FKTYPE	Specify fuel oil, diesel, or kerosene (Categorical Feature)	'1' = 'Fuel oil' '2' = 'Diesel' '3' = 'Kerosene' '4' = 'Fuel oil and diesel' '5' = 'Fuel oil and kerosene' '6' = 'Diesel and kerosene' '7' = 'Fuel oil, diesel, and kerosene' '9' ='Don't know'	Diesel and kerosene = 0.13 Fuel oil and kerosene = 0.20 Fuel oil, diesel, and kerosene = 0.86 Kerosene = 1.52 Fuel oil and diesel = 4.02 Don't know = 18.34 Fuel oil = 23.35 Diesel = 51.58	77.44

Table 2: minimum, mean, median, maximum and percentage of missing values for each numerical feature

	Variable name	Label	Minimum Value	Mean Values	Median Values	Maximum Value	Percentage of Missing Values
1	SQFT	Square footage area	1001	124473.50	20750.00	1500000	0.00
2	NFLOOR	Number of floors	1	3.00	2.00	30	0.00
3	BASEMNT	Number of underground floors	0	0.34	0.0	7	49.63
4	FLCEILHT	Floor to ceiling height (foot)	6	12.87	10.00	60	0.00
5	NELVTR	Number of elevators	1	12.45	3.00	60	67.74
6	NESLTR	Number of escalators	1	6.39	4.00	24	97.28
7	YRCON	Year of construction	1932	1977.00	1981.00	2012	0.00
8	ACT1PCT	Percent used for first activity	0	2.13	0.00	100	94.39
9	ACT2PCT	Percent used for second activity	0	41.29	45.00	100	94.39
10	ACT3PCT	Percent used for third activity	0	33.53	33.00	100	97.44
11	RWSEAT	Religious worship seating capacity	0	22.01	0.00	1800	94.76
12	PBSEAT	Assembly seating capacity	0	88.26	0.00	18000	93.84
13	EDSEAT	Number of classroom seats	0	70.00	0.00	8000	88.76

14	FDSEAT	Food service seating capacity	0	5.81	0.00	700	94.63
15	HCBED	Licensed bed capacity	0	13.70	0.00	300	93.91
16	LODGRM	Number of guest rooms	0	8.38	0.00	1080	95.61
17	NOCC	Number of businesses	0	3.90	1.00	240	0.00
18	MONUSE	Months in use	0	11.32	12.00	12	0.00
19	OCCUPYP	Percent occupancy	0	25.00	0.00	100	71.98
20	LODOCCP	Lodging room percent occupancy	0	2.27	0.00	100	96.56
21	WKHRS	Total hours open per week	0	78.02	60.00	168	0.00
22	NWKER	Number of employees	0	178.78	15.00	6500	0.00
23	HEATP	Percent heated	0	81.49	100.00	100	7.95
24	COOLP	Percent cooled	0	71.68	95.00	100	10.18
25	BOOSTWT	Booster water heaters	0	0.11	0.00	60	93.63
26	XRAYN	Number of X-ray machines	0	0.59	0.00	24	89.88
27	RFGRSN	Number of residential refrigerators	0	6.30	1.00	1000	40.43
28	RFGCOMPN	Number of compact refrigerators	0	9.00	0.00	1200	62.16
29	RFGWIN	Number of walk-in units	0	1.24	0.00	350	69.32
30	RFGOPN	Number of open case refrigeration units	0	1.21	0.00	300	85.65
31	RFGCLN	Number of closed case refrigeration units	0	2.44	0.00	500	72.62
32	RFGVNN	Number of refrigerated vending machines	0	2.24	0.00	300	58.79
33	RFGICN	Number of ice makers	0	2.70	0.00	500	66.28
34	RFGSTP	Percent cold storage	0	0.50	0.00	100	96.24
35	PCTERMN	Number of computers	0	162.92	9.00	4195	3.56
36	LAPTPN	Number of laptops	0	53.00	2.00	1420	3.56
37	PRNTRN	Number of printers	0	49.58	4.00	5000	13.13
38	SERVERN	Number of servers	0	9.49	1.00	600	3.56

39	TVVIDEON	Number of TV or video displays	0		25.51	2.00	240	32.13
40	RGSTRN	Number of cash registers	0		3.95	0.00	500	55.16
41	COPIERN	Number of photocopiers	0		10.51	1.00	1500	40.18
42	LTOHRP	Percent lit when open	0		78.50	90.00	100	4.40
43	LTNHRP	Percent lit off hours	0		15.17	5.00	100	4.97
44	DAYLTP	Percent daylight	0		17.35	5.00	100	3.68
45	MFBTU	Annual major fuel consumption (thousands Btu)	Chosen as Output Features for ANN Model	3.0	17465901.90	39292406.0	1481866360.0	2.47
46	MFEXP	Annual major fuel expenditures ($)		4.0	336921.15	618898.00	36471871.0	2.47
47	ELBTU	Annual electricity consumption (thousands Btu)		0.0	9283680.98	26182500.5	1360596256.0	2.47
48	ELEXP	Annual electricity expenditures ($)		0.0	250045.54	669039.5	35740206.0	2.47
49	NGBTU	Annual natural gas consumption (thousands Btu)		103.0	8627255.97	742971.5	1225754143.0	35.06
50	NGEXP	Annual natural gas expenditures ($)		4.0	60373.00	5570.0	14501641.0	35.06
51	FKBTU	Annual fuel oil consumption (thousands Btu)		0.0	1156019.06	208826.00	96306196.0	77.46
52	FKEXP	Annual fuel oil expenditures ($)		0.0	27926.54	5374.00	2041370.0	77.46

After feature visualization, the problems of missing values and outliers can be handled by making some changes: 1) The features that have missing values more than 75% will be deleted, 2) The features that have low value of missing values is imputed by the median value of feature distribution, and 3) The outliers' values will be replaced by median values. Finally, the data is normalized with respect to maximum value of each feature, the normalization is very important to train weights of neural network [11].

2.3 Model Training and Tuning

After data preparation the step of training ANN weights comes here. So, the data set is separated to three packages: 1) Training data to train model weights, 2) Validation data to tune model weights, and 3) Test data or unseen data to evaluate the trained model. The performance of ANN is depending mainly on model's parameters which called hyper-parameters such as: 1) The learning rate, 2) The number of denes layer, 3) The number of nodes per layer, 4) The loss function, 5) The nodes' activation functions, 6) The metric function, and 7) The Optimizer. The aim of the hyper-parameters tuning step is to find the best hyper-parameters values that return best performance on test data set. To find the best hyper-parameters values by try and error method without consuming time is need experience in the field [13-16].

The trial and error method is used to choose best hyper-parameters for ANN concluded with: 1) Learning rate equal to 4.69e-05; 2) Dense layers equal to 7; 3) Dense nodes per layer equal to 277; 4) Loss function is mean square error (MSE); 5) Activation function for nodes is the rectified linear unit (ReLU); 6) The metric function is mean absolute percentage error which known as best metric function option for prediction energy consumption [17]; and 7) The optimizer selected for training is Adam optimizer because it was found to have significant results with different values of learning rate and different problems in building energy applications [18, 19].

3.4 Evaluate Results

The selected metric to evaluate model is mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and r-squared value. The trained ANN model results are 0.004323, 0.000152, 0.012312 and 0.933945 respectively (Table ٣). The proposed ANN model is also evaluated by comparing to simple linear regression algorithm which give results of 0.0045, 0.000232, 0.015238 and 0.635904 respectively.

Table 3: Comparison between simple linear regression, proposed ANN results and previous work results

Algorithm		Simple Linear Regression	Proposed ANN	Previous ANN [11]	Previous ANN [20]
Number of Input Features		54		8	20
Number of Output Features		6		1	1
Evaluation Metrics	Mean Absolute Error	0.45%	0.4323%	Not Used in Original Paper	Not Used in Original Paper
	Mean Square Error	0.0232%	0.0152%	9.6%	Not Used in Original Paper
	Root Mean Square Error	1.5238%	1.2312%	Not Used in Original Paper	Not Used in Original Paper
	R-Squared	0.635904	0.933945	Not Used in Original Paper	0.82

The comparison declared in (Table 3) is showing the power of proposed ANN, especially in comparison with previous work on same data. The main drawback in the previous work that reduce performance is the conversion of all numerical feature to categories which reduce accuracy of predicting specific value, in addition to they drop some important features without study the effect of each one on the output features. In this paper the data is handled as a combination between numerical and categorical features, so the model gives low error and high prediction accuracy comparing to linear regression and previous work on the same data.

4. Conclusion

This paper introduce description for ANN implementation in buildings energy prediction field which have high degree of complexity because of the non-linear relation between features in the field. The ANN algorithm have high degree of flexibility to deal with different cases by handling hyper-parameters of it. The proposed ANN algorithm have hyper-parameter values as following (learning rate value is 4.6895e-05, number of dense layers is 7, number of dense nodes per layer is 277, loss function is MSE and activation function is (ReLU). This hyper-parameters values give high performance comparing to simple linear regression algorithm for prediction of multi-output values where the trained ANN model results are 0.0045 for MAE, 0.000232 for MSE, 0.015238 for RMSE and 0.933945 for r-square value while the simple linear regression algorithm gives results of 0.0045 for MAE, 0.000232 for MSE, 0.015238 for RMSE and 0.635904 for r-square value. In addition, the comparison between proposed model and previous work on the same data declare the high performance of the proposed one. The conclusion declare that the proposed ANN model is a powerful prediction tool to be used in the energy and building field.

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