Quantum Hybrid Echo state networks to model energy efficiency of residential area

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Introduction

Energy consumed by buildings have been rapidly enhancing across the globe [1]. As per laws at certain countries [2] energy efficient dwellings are essential for maintaining energy transition as well as to sustain controlled environmental conditions. Simulation tools are used mostly to calculate energy consumption so as to manage energy constraints in an effective manner. However, alterations in such simulation software drivers or packages may cause mismatches and strive from accurate results. For energy savings, energy efficient modelling of residential buildings is necessary [3]-[4], in this work a framework is proposed so as to consider physical parameters of a building [5] in order to predict the important factors (heating load (HL) and cooling load (CL)) which are useful to make an energy efficient residential area.

Echo state networks [6] are a faster version of Recurrent neural networks that do not include back-propagation, have lesser trainable parameters and does not incur vanishing gradient issues. A reservoir layer is followed by quantum gates so as to make computations faster and hence enhances the reliability of the architecture pertaining to real-time energy efficient calculations of not only a single residential area but may be extended to larger areas as well.

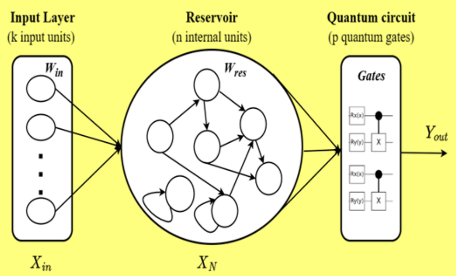

Fig. 1. Scheme of the proposed architecture.

Experimental setup

In the proposed model, the readout layers are replaced by quantum-gates, reducing even the minimum training requirement. The involved quantum-qubits offers much ease in minimizing the losses inculcating diverse values obtained using rotation gates acting on the parameters and hence attaining high accuracy in the required task. The proposed architecture is used to predict HL and CL based on input parameters namely surface area, roof area, wall area, concretely, relative compactness, overall height, glazing area orientation and glazing area distribution. Here, two-qubits are used to develop the hybrid model since the architecture was used to predict two values that is the Heating load and cooling load respectively. The final dense layer output is passed as a parameter to the variational quantum circuit as shown in Fig:2 after encoding the classical data into quantum state $|\psi\rangle$ using a feature map function F given by:

$$|\psi(x)\rangle = F(x)(|0\rangle)^{\otimes 2}$$

After creating quantum states, these are passed to a combination of gates.

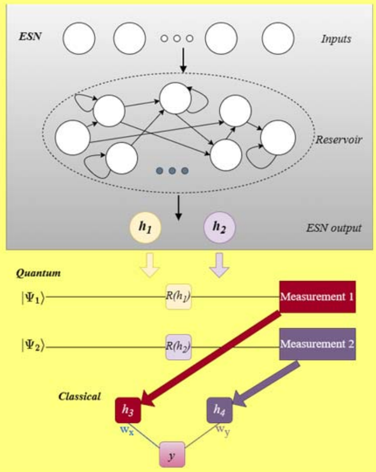

Fig. 2. View of the architecture details.

Experiment

The proposed architeture was used to compute the Heating load for a residential area based upon some constraints of a building. As shown in Fig:3, the hourly prediction of the heating demand was nearabout same as that of the actual value. The proposed model was found to be tolerant to noise and errors and showed improved performance as compared to normal ESN model. In future, we hope that the datasets can be made diverse and interdisciplinary so as to incorporate the hybrid architecture in various electronics products. Many such applications, can be implemented easily using the proposed model with enhanced accuracy and performance in a fraction of seconds integrating with a gadget based user-friendly application

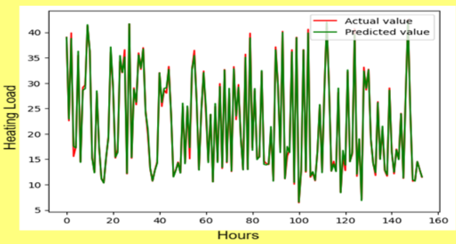

Fig. 3. Hourly prediction of Heating load in a residential area using the proposed architecture.

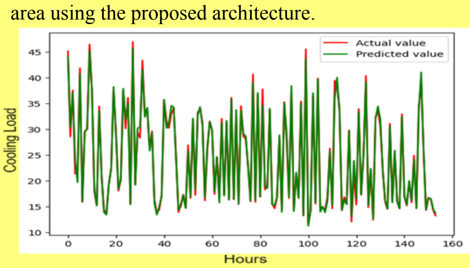

Fig. 4. Hourly prediction of Cooling load in a residential area using the proposed architecture.

Results

The proposed approach was analyzed based upon the coefficient of determination R2, root mean square error (RMSE) as well as mean absolute error (MAE). The ESN-QC model was evaluated based upon the above mentioned parameters and was compared with other machine-learning models [5] as depicted in Tab.1 and Tab 2. for the Heating load and Cooling load calculation respectively.

With the high accurate prediction, the proposed systems can be beneficial to extend the residential area to a broader aspect and hence promote efficient utilisation of energy based upon consumer usage and it can serve as a basis to facilitate the transmission of energy based information to users in energy management.

Table 1. Coefficients of determination (R^2), correlation coefficients (r), RMSE and MAE value comparison of proposed model with other models for the Heating load (HL) factor and for testing data.

Model	R^2	R	RMSE	MAE
ESN-QC	**0.9967**	**0.9985**	**0.5628**	**0.3167**
MARS	0.9961	0.9981	0.6899	0.5709
SVM linear	0.9380	0.9685	2.7327	2.0413
MLP	0.9893	0.9946	1.5663	1.3396
M5 model	0.9348	0.9668	0.7639	0.5573

Table 2. Coefficients of determination (R2), correlation coefficients (r), RMSE and MAE value comparison of proposed model with other models for the Cooling load (CL) factor and for testing data.

Model	R^2	R	RMSE	MAE
ESN-QC	**0.9960**	**0.9951**	**0.6280**	**0.4127**
MARS	0.9651	0.9824	1.8111	1.2884
SVM linear	0.8968	0.9470	3.2106	2.2672
MLP	0.9374	0.9682	1.8553	1.3774
M5 model	0.9599	0.9797	1.8230	1.3370

Conclusions

In this work, we reported a hybrid model using ESN and quantum gates which was used for the energy efficiency analysis of residential area based upon certain physical parameters. The hybrid ESN-QC obtained coefficients of determination equal to 0.9967 for the HL estimation and 0.9960 for the CL estimation when this framework was applied 768 diverse residential buildings, respectively, showing improved performance when compared to other state-of-the-art models. The idea can be extended to much larger location for faithful controlling energy aspects leading to proper consumption of the same and avoiding misuse.

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