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Hyperparameter optimization of artificial neural network in building energy simulation

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Artificial Neural Networks (ANNs) play a significant role in emulating Building Energy Simulation (BES), forecasting building energy consumption, and optimizing energy retrofit measures. The determination of the appropriate ANN's architecture is a complex issue. Hyperparameter optimization (HPO) involves aligning ANN prediction results with data to achieve optimal performance by tuning the ANN's hyperparameters. This method is applied to retrofit an existing low-energy building. To construct the ANN for retrofit measures, data obtained through Latin Hypercube sampling are utilized. The ANN is used to predict the hourly energy consumption, the hourly energy generation, and thermal comfort in the retrofit scenario. The results underscore the importance of HPO in achieving predictions with an ANN, demonstrating an R^2 error exceeding 0.9.

KEYWORDS: hyperparameter optimization, building energy simulation, artificial neural network, machine learning, building retrofitting

Les réseaux neuronaux artificiels (RNA) jouent un rôle significatif dans l'émulation de la simulation énergétique des bâtiments (BES), la prévision de la consommation d'énergie des bâtiments et l'optimisation des mesures d'amélioration de l'efficacité énergétique. La détermination de l'architecture appropriée pour les réseaux neuronaux artificiels dans l'émulation de BES est une question complexe. L'optimisation des hyperparamètres (HPO) consiste à aligner les prédictions des ANN sur des données afin d'obtenir des performances optimales en ajustant les hyperparamètres de l'ANN. Cette méthode est appliquée à la rénovation d'un bâtiment existant à faible consommation énergétique. Les données obtenues par échantillonnage hypercube latin sont utilisées pour construire l'ANN pour les mesures de rénovation. Le RNA est utilisé pour prédire la consommation d'énergie horaire, la génération d'énergie horaire, et le confort thermique dans le scénario de rénovation. Les résultats soulignent l'importance de l'optimisation des hyperparamètres pour obtenir des prédictions avec un RNA, démontrant une erreur R^2 dépassant 0,9.

MOTS CLES : optimisation des hyperparamètres, simulation énergétique des bâtiments, réseaux neuronaux artificiels, apprentissage automatique, rénovation des bâtiments

1. INTRODUCTION

According to the French Agency for Ecological Transition (Ademe, 2023a), the building sector accounts for 44% of the total energy consumed in France, making it a significant contributor to global energy consumption. Estimates indicate that new buildings represent less than 2% of the entire building stock (Ademe, 2023b). Consequently, building energy retrofitting has been proposed as a solution to mitigate high energy consumption in buildings.

In this context, Building Energy Simulation Optimization (BESO) is employed to reduce building energy consumption by incorporating retrofit measures (Pan et al. 2023). To assess whether the optimization algorithm has achieved convergence, the hypervolume, an indicator developed by Zitzler and Thiele (Eiben 1998), could be used to evaluate the convergence conditions. This indicator calculates the volume of the hypercube formed by optimal solution in the objective space. Typically, achieving convergence of this indicator requires approximately 1000 iterations of Building Energy Simulation (BES) (Harkouss, Fardoun, and Biwole 2018b; 2018a). Conducting an annual simulation with the BES model could take 16 minutes, resulting in a significant computational burden of approximately 11 days for optimizing the model (Zhan, He, and Huang 2023; Bre, Roman, and Fachinotti 2020). Hence, BESO incurs a high computational cost. To alleviate this computational burden, meta-modeling is proposed.

Meta-modeling is a stochastic approach utilized to capture the correlation between the input and output of the building energy model, facilitating the creation of a computationally lighter model. Meta models allow for more efficient exploration of the parameter space, enabling rapid analysis of various scenarios and configurations. This capability can be particularly valuable in optimization tasks or when investigating complex system behaviors. Additionally, these models can be seamlessly integrated with optimization algorithms, allowing for automated parameter tuning and optimization. This integration streamlines the optimization process and can lead to faster convergence to optimal solutions.

Artificial Neural Network (ANN) is a machine learning model, which serves as meta-model to emulate building energy simulation (BES). This model comprises a collection of connected units or nodes known as neurons. Analogous to synapses in a biological brain, each connection can transmit a signal from the receiving neuron to neighboring neurons. In each connection, the output is computed by a nonlinear function of the inputs called the activation function. Defining all these mentioned hyperparameters, such as the number of neurons, activation function type, and number of hidden layers, contributes to constructing the architecture of the ANN. This study applies a new framework used to optimize the hyperparameters of ANN for emulating BES in building energy retrofitting.

2. BASE CASE STUDY CHARACTERIZATION

The base case study is a low-energy residential building as depicted in Figure 1, located in Cébazat village near Clermont-Ferrand City in France. The building was constructed in 2010 and comprises three floors, housing 18 apartments with a total area of 1599.2 m². This building was chosen due to the availability of experimental data.



Figure 1 : Exterior view of the base case study

Table 1 presents the thermo-physical characteristics of the building's envelope. The external walls insulation material is Xtherm Itex 32E expanded polystyrene (Anon 2023), with a thermal resistance of $R= 3.4 \text{ m}^2\text{K/W}$. The roof is constructed with a wooden framework and topped with roman tiles, incorporating cellulose fiber insulation with a thermal conductivity of $0.125 \text{ W/m}\cdot\text{C}$. For the windows, insulating double glazing filled with argon (4/16/4) is utilized, of U-value of $1.4 \text{ W/m}^2\cdot\text{C}$ and a PVC frame.

Components	Layers (Out to in)	U-value coefficient ($\text{W/m}^2\cdot\text{C}$)
External wall	1 cm wood cladding	0.12
	15 cm expanded polystyrene	
	18 cm Concrete	
	10 cm expanded polystyrene Plaster (BA13)	
Internal wall	18 cm Concrete	0.25
	15 cm expanded polystyrene	
Ground floor wall	23 cm Concrete deck	0.3
	15 cm Extruded polystyrene	
Roof	20 cm insulation material ($U=0.125 \text{ W/m}^2\cdot\text{C}$)	0.16
	1.3 cm Timber concrete	
Windows	Double glazing with argon 4/16/4	1.4

Table 1: Thermo-physical properties of building's envelope

3. METHODOLOGY

3.1. DEFINING NEURAL NETWORK INPUT PARAMETERS IN BUILDING ENERGY SIMULATIONS

After calibrating the TRN Build (TRNSYS ,2022) for the base case study using measured data, various retrofit measures are incorporated. The integrated passive and renewable retrofit measures on TRNSYS, are then employed as input parameters to construct the ANN model. In addition to the retrofit

measures, weather data and timestep are included. The input parameters adopted for building the ANN model are presented in Table 2.

Parameter Category	Parameter Type	Parameters
Time	Timestep	Hourly time step
Weather condition	Weather data	Ambient temperature Relative humidity Total solar radiation Wind speed Wind direction
Retrofit measures	Passive retrofit measure	External wall insulation thickness Window U-value Roof wall insulation thickness Heating setpoint temperature
	Renewable retrofit measure	Number of Photovoltaics Number of solar collector Number of domestic wind turbines

Table 2: Description of the adopted input parameter for neural network

3.2. MODEL SAMPLING

To train the ANN meta-model, data are required. Therefore, Latin Hypercube Sampling is adopted to provide data by generating samples of the BES, executing different sets of building parameter values for each one. Latin Hypercube sampling is a method employed to sample complex models, being the most widely used random sampling method for data generation and sampling within BES (Roman et al. 2020).

During sampling, the integrated yearly weather data remains the same across all yearly simulations. Each weather file comprises 8760 hourly weather data points spanning a year. Each retrofit scenario is simulated based on these 8760 hours. Subsequently, set of scenarios are sampled across multiple simulations. In essence, the simulated retrofit scenarios vary across simulations in accordance with the changing weather data throughout the year. In each simulation, the objective functions chosen in this study are:

- Hourly Energy Consumption
- Hourly Energy Generation

- Hourly Predicted Mean Vote (PMV)

3.3. HYPERPARAMETER OPTIMIZATION

Hyperparameter optimization (HPO) is a crucial step to ensure the optimal performance of deep learning algorithms, particularly in determining the architecture of ANN for emulating BES. Numerous methods have been developed to execute HPO to search for the suitable ANN architecture. (Morales-Hernández, Van Nieuwenhuysse, and Rojas Gonzalez 2023) conducted a survey on recent HPO algorithms for deep learning. It was concluded that the covariance matrix adaptation evolution strategy (CMA-ES) optimization algorithm stands out as one of the best for addressing single-objective HPO. CMA-ES is particularly effective for optimization problems characterized by non-linear, non-convex, noisy, or explicitly structure-lacking objective functions (Elsken, Metzen, and Hutter 2019). This algorithm is implemented in the Python programming language using the Optuna framework (Akiba *et al.* 2019).

In addressing HPO problems, data are partitioned into three datasets: training, validation, and testing. The training data is utilized to train the proposed model during each iteration of the optimization process. Validation data is employed to assess the performance of the trained model, and after optimization, testing data is used to evaluate the accuracy of the optimal model architecture.

The determination of learning rate, the number of neurons per hidden layer, the number of hidden layers, the type of optimizer, the activation function, and the batch size, is conducted to ascertain the hyperparameters of the ANN model. The implementation of the ANN is carried out using the Python programming language with PyTorch (Paszke *et al.* 2019), a deep learning library for Python.

4. RESULTS AND DISCUSSION

The computation is completed using a standard laptop computer (CPU: Core i5 12500H @ 2.50 GHz, GPU: NVIDIA T600, RAM: 32GB). The GPU is utilized for training and validation as it outperforms the CPU in computational time.

Regarding meta model construction, to determine the number of samples According to Jones, Schonlau, and Welch (Jones, Schonlau, and Welch 1998), it is advisable to ensure that the simulation dataset consists of at least ten times more instances than the number of inputs for black box models. Since our ANN model utilizes 7 retrofit measures, a total of 70 yearly simulations would be sufficient to build the model. However, in this case, 200 yearly simulations were used to develop the model, meaning 2 days. Then, optimizing the hyperparameters consumes 4 days. Hyperparameter optimization is performed once for all, and the optimal model is obtained as outlined in the conference article. Then, Training the model incurs a time cost of about 1 hour. Subsequently, the model simulates each building case studied, with a computational cost of 10 seconds per yearly simulation (iteration). Therefore, running the model for 1000 iterations would require approximately 166.7 minutes (3 hours). This approach allows the model to be trained for any building case studied, and then the parameters can be optimized, thus lowering the computational burden of optimization.

Table 3 presents the optimal values of hyperparameters that are used to train and validate the ANN. The results indicate that a five-layer ANN model with 253 neurons and Gelu activation function,

utilizing the 'Adam' optimizer with a Learning Rate of 0.001, provides the best prediction performance in both tasks.

Hyperparameter	Optimal Value
Number of hidden layers	5
Number of neurons in hidden layer	253
Type of activation	Gelu function
Type of optimizer	Adam optimizer
Batch size	50
Learning rate	0.001

Table 3: Optimal values of ANN's hyperparameter

The average of the three outputs (consumed energy, generated energy, predicted mean vote) mean square loss during iterations is depicted in Fig. 2. The loss remained constant from the 215th generation in training. The results imply a good convergence performance of the ANN model.

The achieved R² errors for consumed energy, generated energy, and predicted mean vote are 0.99, 0.98, and 0.9, respectively. These values demonstrate a highly precise model in comparison to (Ascione *et al.* 2017) where the R² error for energy consumption is reported as 0.96. Hence, the results underscore the importance of hyperparameter optimization in improving the architecture in ANN to emulate BES.

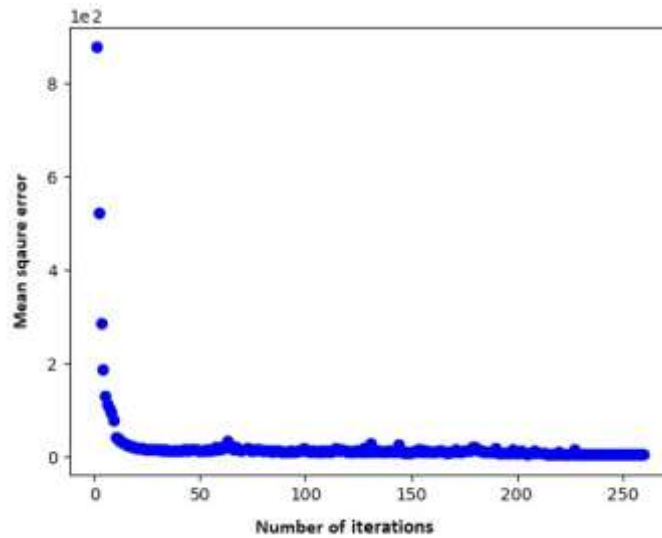


Figure 2: Mean square error loss of ANN per number of iterations

5. CONCLUSION

Building Energy Simulation (BES) is essential for assessing building energy efficiency, offering guidance for sustainable design decisions, and optimizing energy retrofit measures. However, optimizing BES involves a substantial computational burden. To alleviate this burden, an ANN is proposed as a meta-model to replace BES. HPO is employed to identify the optimal hyperparameters of the ANN with highest accuracy. The obtained R^2 errors for consumed energy, generated energy, and predicted mean vote are 0.99, 0.98, and 0.9, respectively. These results underscore the importance of hyperparameter optimization in enhancing the architecture of ANN. As future prospect built meta model will be used to investigated building retrofitting measures in 10 different locations for the climates of 2024, 2050 and 2080, thus producing thousands of simulations.

Future studies should concentrate on multiple outputs by expanding upon multi-objective HPO for ANN. ANNs can be developed to predict multiple outputs, and the model should be optimized based on the errors in predictions across various ANN outputs compared to real data. Moreover, HPO can be extended to different machine learning models, including Support Vector Machines, polynomial regression, Convolutional Neural Networks, and Recurrent Neural Networks.

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