Estimating peak water demand using Neural Networks

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Abstract

Current methodologies for estimating simultaneous peak water flow (SPWF) employ deterministic, probabilistic, and stochastic approaches. However, most methods fall short in adequately capturing the uncertainties inherent in real-world scenarios, such as building occupancy and user behaviour. Leveraging the advancement and versatility of machine learning, this study introduces and evaluates the use of neural networks as a novel solution for SPWF estimation. Different kinds of neural network architectures are evaluated: ANN, CNN, RNN, and hybrid neural networks. The models were based on two methods: Wistort's method which is probabilistic, and the Water Demand Estimation Model (WDEM) which uses a stochastic technique based on Hunter's method. Hyperparameter tuning techniques were employed to optimise model performance, and the models were validated against real-world measurements and with established standards such as the CIPHE Design Guide and the British Standard (BS8558). Results from the evaluation prove that ANN and Hybrid CNN-RNN produce the best computer models for the stochastic-based methodologies. This study pioneers the utilization of data-driven methodologies for computing peak simultaneous water flow in buildings, aiming to address the overestimation challenge through the implementation of highly flexible and adaptable models that can account for uncertainties in water use.

Keywords

Water demand; Neural Networks; ANN; CNN; RNN.

1 Introduction

Simultaneous peak water flow (SPWF) estimation forms a cornerstone in enabling decarbonisation of water systems in the built environment. Improving the accuracy of SPWF estimations can mitigate issues such as wasteful water usage, the proliferation of legionella, plumbing material wastage, and inefficient energy use for water. This study aims to pioneer the integration of neural networks and deep learning techniques to devise novel approaches for SPWF estimation. By harnessing the capabilities of data-driven methodologies and advanced computational techniques, this research opens new avenues for enhancing SPWF estimation accuracy.

Current models used in design codes are mostly probabilistic or empirical (Jack *et al.*, 2017). Meanwhile more recent model developments, although not yet adopted into building codes, use a mix of probabilistic and stochastic models, such as Murakawa's Simulation for Water Consumption (MSWC) (Wu, Sakaue and Murakawa, 2017), SIMDEUM (Blokker, Vreeburg and van Dijk, 2010), and the Water Demand Estimation Model (WDEM) (Mohammed, 2022) among others. These models have significantly reduced the overestimation of peak water demand. Nonetheless, most of these methods rely on survey data to scale and determine factors in the calculation, such as occupancy patterns, water use probability, water flow rates and pulse duration, which are expected to evolve over time. Therefore, there is a need to make these models more flexible and adaptable to accommodate these changes, while still reducing overestimation.

This study aims to investigate the viability of neural networks for estimating SPWF, and to measure the accuracy of the neural network models against two established models. This work also evaluates whether the complexity of neural networks can be offset by the benefits it offers in terms of flexibility and accuracy, especially for non-residential buildings. The computer models developed take the fixture use probability values of each fixture type as inputs, and the SPWF value as output.

2 Review of Current Models

Table 1 presents a summary of the different SPWF estimation methods developed since Hunter's work on fixture unit method in 1940 (Hunter, 1940). The transition from probabilistic to stochastic methods indicates a significant shift towards more effective modelling of uncertainties associated with water use. It is worth noting that recent advancements tend to focus on the analysis of residential buildings, potentially due to the accessibility of data for model refinement and validation purposes.

Table 1 – Summary of Some Peak Water Demand Estimation Methods and Models

Model (Author)	Model Type	Methodology	Scope
Fixture Unit Method (Hunter, 1940)	Probabilistic	Binomial probability distribution	Residential
Wistort's model (Wistort, 1994)	Probabilistic	Normal approximation for the binomial distribution	Residential
Water Demand Calculator (Buchberger *et al.*, 2017)	Probabilistic and other statistical methods	Combination of Modified Wistort method, Exhaustive enumeration, q1+q3 method	Residential
SIMDEUM (Blokker, Vreeburg and van Dijk, 2010; Blokker *et al.*, 2011)	Stochastic	Based on the Poisson-rectangular-pulse (PRP) (Buchberger and Wu, 1995) model; with probability distributions for water use frequencies, durations, and intensities; Use of statistical information for diurnal water use, and appliances	Residential and Non-residential
Murakawa's Simulation for Water Consumption (MSWC) (Murakawa, 1985; Murakawa *et al.*, 2005)	Stochastic	Queuing theory-based using probability distributions for modelling water usage, and Monte Carlo simulation to produce high-resolution time-series water demand	Residential and non-residential
Water Demand Estimation Model (WDEM) (Mohammed, 2022)	Stochastic	Binomial distribution-based Monte Carlo simulation, which considers maximum occupancy	Non-residential
(Josey and Gong, 2023)	Stochastic	Combination of SIMDEUM, fixed intensity values from Buchberger *et al.*, (2017), and fixture p-values from Omaghomi *et al.*, (2020)	Residential
(Cortez-Lara *et al.*, 2024)	Stochastic	Based on Inverse Transform Method (ITM) with binomial distribution and Monte Carlo simulation	Residential

This study focuses on Wistort's model and the WDEM. Wistort's model was selected for its independence from fixture or loading units, eliminating the need for recalibration. Instead, the method takes into account the physical parameters in water use, namely the number of fixtures, fixture use probability, and the water flow rate of each fixture type. Consequently, Wistort's method maintains relevance amidst evolving water fixture technologies and changes in water consumption patterns.

Meanwhile the WDEM incorporates a binomial probability distribution model, considering thousands of possible scenarios through Monte Carlo simulation. This approach addresses the uncertainties related to occupancy and water use behaviour, while the use of the binomial probability distribution maintains the simplicity and use of the Bernoulli trial in the model.

2.1 Wistort's model

Robert Wistort developed a peak water demand estimation model in 1994 as a modification of Hunter's method, by applying a normal approximation to the binomial distribution (Omaghomi, 2014). This development eliminates the reliance on fixture units, which is one of the causes of overestimation in Hunter's method. In this model, the number of busy fixtures (X) is a random variable with a binomial distribution with a mean and variance of

$$u = E[X] = np = n\frac{t}{T} \tag{1}$$

$$\sigma^2 = Var[X] = np(1-p) = \frac{nt(T-t)}{T^2}, \tag{2}$$

respectively, where u is the mean number of busy fixtures at any given time during peak period, σ^2 is the variance of the busy fixtures, n is the total number of fixtures of a given type, p is the probability that a fixture is running (and therefore in use) during the peak period, t is the average demand duration, and T is the average time between successive operations of the fixture.

Using the normal approximation for the binomial distribution (NABD) and for K independent fixture groups, Wistort defined the peak water demand (Q) to be the 99th percentile of the total demand given by

$$Q_{0.99} = \sum_{k=1}^{K} n_k p_k q_k + (z_{0.99})\sqrt{\sum_{k=1}^{K} n_k p_k (1-p_k) q_k^2} \tag{3}$$

where K is the total number of fixture groups, n_k is the number of fixtures for a specific fixture group, p_k is the probability that a fixture is being used, q_k is the fixture flow rate, and $z_{0.99}$ is the 99th percentile of the standard normal distribution.

2.2 WDEM

The WDEM is a relatively new model developed in 2022 at Heriot-Watt University. This model aims to yield design equations for estimating the SPWF by using the maximum occupancy in non-residential buildings (Mohammed, 2022). It uses a Monte Carlo simulation applied to the binomial probability distribution. This part of the methodology from the WDEM will be used in this study. Simulations with 400,000 trials were performed to consider all possible scenarios in small to large scale non-residential buildings. In this method, the number of fixtures in use (X) per fixture type in a trial is given as

$$P(X = k) = \binom{n}{k}(p)^k(1-p)^{n-k} \tag{4}$$

where n is the total number of fixtures per type, p is the probability that the fixture is in use, $\binom{n}{k}$ is the binomial coefficient, and $(1-p)^{n-k}$ is the probability of the fixture not being in use. The total flow rate is obtained as

$$Y = \sum_{k=1}^{K} X_k * q_k \ , \tag{5}$$

summing over all K fixtures. The estimate of the 99th percentile, $Q_{0.99}$, of Y is obtained using Monte Carlo as follows: Simulate M=400,000 samples of Y, say $Y_1, Y_2, \dots, Y_M$, and then estimate $Q_{0.99}$ as $Y_{(0.99*M)}$ where $Y_{(k)}$ is the k^{th} order statistic of Y-samples.

3 Neural Networks for Peak Water Demand Estimation

The use of neural networks aims to produce a computer model (η) for estimating the SPWF through regression. The dataset for model training was produced as theoretical values based on Wistort's model and the WDEM. The two models were chosen for the following reasons:

- the availability of aggregated water consumption data compared to end-use water consumption data especially for non-residential buildings,
- the flexibility of both methods such that they can be used for additional types of fixtures (in contrast to Hunter's model which requires fixture units), and
- the applicability of both models to buildings with a high number of fixtures.

Obtaining end-use water consumption or micro-component data is also not often practised compared to setting up water meters for whole households or whole buildings. This reinforces the practicality, applicability, and verifiability of the method. Comparing and using the results of the two methods also makes use of the advantages and offsets the disadvantages of the simulation-based and analytical-based methodologies.

In determining the best models, each model type was optimised by tuning the hyper-parameters and varying the input configuration. The number of layers and neurons were also tuned to find the optimal model. Python 3.11 was used for model development, and the TensorFlow (Martín Abadi *et al.*, 2015) library was used for the neural network. The model's goodness-of-fit was measured through its R-squared statistic, otherwise known as the coefficient of determination.

3.1 Dataset Generation

A theoretical dataset was generated for the neural network model training. In generating the dataset, building information and water fixture information was first determined. Building plans were used to obtain the total floor area and the number of water fixtures in the building. Visits to the buildings were also conducted to confirm the fixture installation, especially for the white goods such as dishwashers. The fixture flow rates were obtained from the WDEM, since these values were confirmed for these buildings during the original study (Mohammed, 2022).

The inputs in the datasets comprised the number of fixtures per type ($\boldsymbol{n}$), and a grid of all possible combinations of fixture use probabilities ($\boldsymbol{p}$), with each probability ranging from 0 to 0.2 with a 0.02 interval. The choice of this range was determined through engineering knowledge and generalisation from other surveys. The datasets were limited to 50,000 rows to limit the calculation time, considering that the computations were performed in computers with 8GB or 16GB RAM, and 4 CPU cores.

Two datasets were then produced for each building – one with $Q_{0.99}$ values computed by Wistort's method, and the other with $Q_{0.99}$ values computed using the WDEM. For the same computing constraints, the trials for the WDEM were reduced to 1500. Only the p-values were used as inputs for the neural network, with the Q-values as output.

3.2 Neural Network Architectures for Evaluation

The following neural networks were evaluated for efficiency. These architecture types are some of the most basic types used when implementing neural networks, with the addition of a hybrid neural network which has seen a rise in different applications, including those that factor in human behaviour (Yan *et al.*, 2019).

3.2.1 Artificial Neural Network (ANN)

The simplest type of neural network is the ANN, also called multi-layer perceptron (MLP) or feed-forward neural network (FNN). Each layer (l) of the network is composed of a set of artificial neurons that have the same activation function ($f^{(l)}$) (Benois-Pineau and Zemmari, 2021). The neuron is the basic unit in a neural network that receives the input signals ($x_1, x_2, \ldots, x_n$) and applies an activation function f. A vector of weights ($\omega_1, \omega_2, \ldots, \omega_n$) determines the strength and influence of each neuron in a network, and a bias (b) is applied to offset the value. An output neuron (y) can be defined as shown in Equation 6.

$$y = f(z) = f\left(\sum_{i=1}^{n} \omega_i x_i + b\right) \tag{6}$$

A deep neural network is an ANN with at least one hidden layer. For any $1 < l < L$, the vector outputs $\boldsymbol{y}^{(l)}$ of the layer l can be expressed as

$$\boldsymbol{y}^{(l+1)} = f^{l+1}\left(\omega^{(l)^T}\boldsymbol{y}^{(l)} + \boldsymbol{b}^{(l+1)}\right) \tag{7}$$

given an ANN with $L > 0$ layers (Benois-Pineau and Zemmari, 2021).

3.2.2 Convolutional Neural Network (CNN)

CNN was originally designed for image processing and is still widely used for the same application. As such, the layers of a CNN are designed so that the neurons are arranged in three dimensions (height, width, and depth) to match the geometric shape of the image data (Benois-Pineau and Zemmari, 2021). The convolutional layer is the fundamental component of CNN where the convolution operation is performed. Convolution in the context of neural networks is a linear operation that involves the multiplication of a set of weights with the input (Brownlee, 2019).

3.2.3 Recurrent Neural Network (RNN)

For the RNN, the output neuron is affected by both the current and previous inputs. The decision of the network at time t is influenced by the decision made in the previous time step at $t-1$ (Benois-Pineau and Zemmari, 2021). The dependence on the previous time point can be expressed as shown in Equation 8.

$$y^{(t)} = f\left(y^{(t-1)}, x^{(t)} \right) \tag{8}$$

In the training process, RNNs use a Backpropagation-Through-Time (BPTT) strategy which obtains gradients during training and connects the neurons' output to their inputs (Gruslys *et al.*, 2016). BPTT works by “unfolding” the NN through time, creating copies of the recurrent units that can be treated as a deep feed-forward network with tied weights (Gruslys *et al.*, 2016). However, RNNs suffer from the exploding gradient problem as the BPTT depends exponentially on the weights for each timestep, and therefore fails to learn information after around 5-10 timesteps (Gers, Schmidhuber and Cummins, 1999). Long Short-Term Memory (LSTM) overcomes this problem by introducing a linear unit (cell), called the Constant Error Carousel which is used for error flow control using the concept of gates (Han *et al.*, 2021).

3.2.4 Hybrid CNN-LSTM

Feature extraction capabilities of the CNN and the ability of LSTM to recognize patterns in the data make a Hybrid CNN-LSTM model effective for regression problems. It is seen as an improvement to the commonly implemented neural network and was deemed the most efficient model in applications such as load forecasting, classification, and anomaly detection among others. Its efficiency in predicting water flow will be evaluated in this study.

3.3 Hyperparameters Tuning

Hyperparameters tuning was performed for each neural network architecture to determine the best model configuration. With the help of Scikit-Learn’s (Pedregosa *et al.*, 2011) Grid Search Cross-Validation (GridSearchCV) function, which is an exhaustive search algorithm that runs the model with every combination of the parameters provided, the best model configuration is identified according to the chosen evaluation parameter. At least two options for each hyperparameter were used for the tuning, including the number of neurons per layer, the type of activation layer, learning batch size, kernel size, and filter size.

4 Results and Discussion

Two non-residential buildings were used for the case study to prove the applicability of neural networks in peak water demand estimation. The first building is the Estates Building, a two-storey office building located in Heriot-Watt University, and the second building is the Post-Graduate Centre which is a three-storey mixed-use building with lecture halls, café, offices, and social area. Table 2 summarizes the water fixtures in the two buildings, together with the corresponding flow rates, and counts. Without the 50,000-dataset limit, both buildings would have had 3,628,800 datapoints with the nine fixture types.

Table 2 - Fixtures Information for Estates Building

Fixture Name	Fixture Flow Rate (L/s)	Estates Building Count	Post-Graduate Centre Count
Bidet	0.150	0	2
Cleaner's Sink	0.130	1	2
Dishwasher	0.083	1	4
Kitchen Sink - Mixer Tap	0.133	2	1

Kitchen Sink - Separate Tap	0.150	3	0
Shower	0.101	1	2
Urinal	0.055	2	10
WC	0.053	9	24
Washbasin - Mixer Tap	0.083	5	4
Washbasin - Separate Tap	0.057	3	18

As shown in Figure 1 and Figure 2, the neural network architectures were able to produce computer models that approximate the $Q_{0.99}$ values from the WDEM for the chosen grid of p from 0 to 0.2, as reflected in their R-Squared values. Note that the percentiles from the WDEM method do not have a close mathematical expression; thus, the analytical approximation of the ANNs to these values are noteworthy. The hyperparameters for each model are also indicated in the results. The results from these figures are for the test dataset, which comprises 10% of the whole dataset. The models were trained using 80% of the dataset, while the remaining 10% was used for validation. The models were checked for overfitting through the validation dataset.

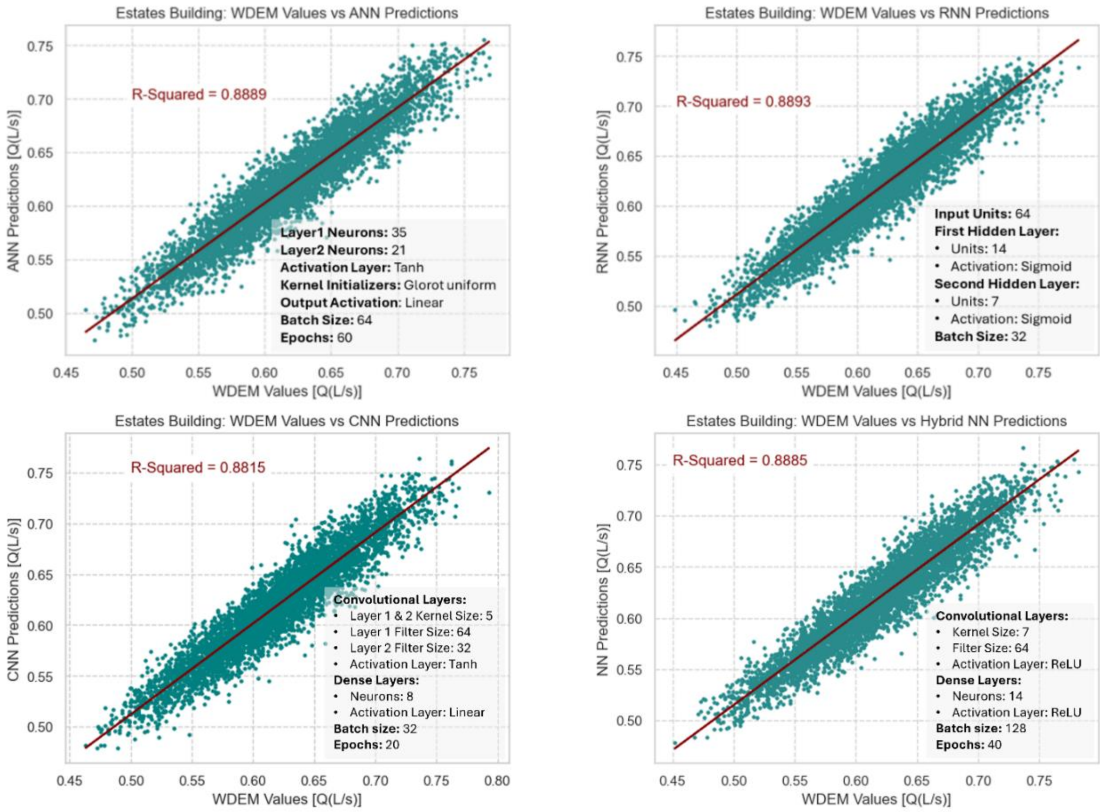

Figure 1 – WDEM-based model results for Estates Building

The Estates Building models have lower R-squared values overall, indicating that the data did not fit the regression model as well as for the other building. As the number of input neurons between the two models were similar, as well as the hyperparameters used for tuning, the differences can be attributed to the random sampling of the dataset to reduce it to 50,000 rows. The average Q-value of the Estates Building (0.6206 L/s) is also lower than the Post-Graduate Centre (1.0227 L/s), which would have affected the model as there was no standardisation or normalisation performed. For both buildings, the ANN and Hybrid CNN-LSTM architecture produced the best estimations. As the data does not have a particular pattern to be learned by an LSTM, or feature and class to be learned by CNN, the simpler architecture of an ANN was sufficient in producing a good model to estimate the Q values.

Meanwhile being based on a probabilistic model, the Wistort-based neural network models had R-squared values close to one, as shown in Figure 3 and Figure 4. These results reinforce the efficacy of neural networks as computer models for SPWF estimation. For the Wistort-based models, the RNN models gave the best fit with R-Squared values of 1.0 and 0.9999.

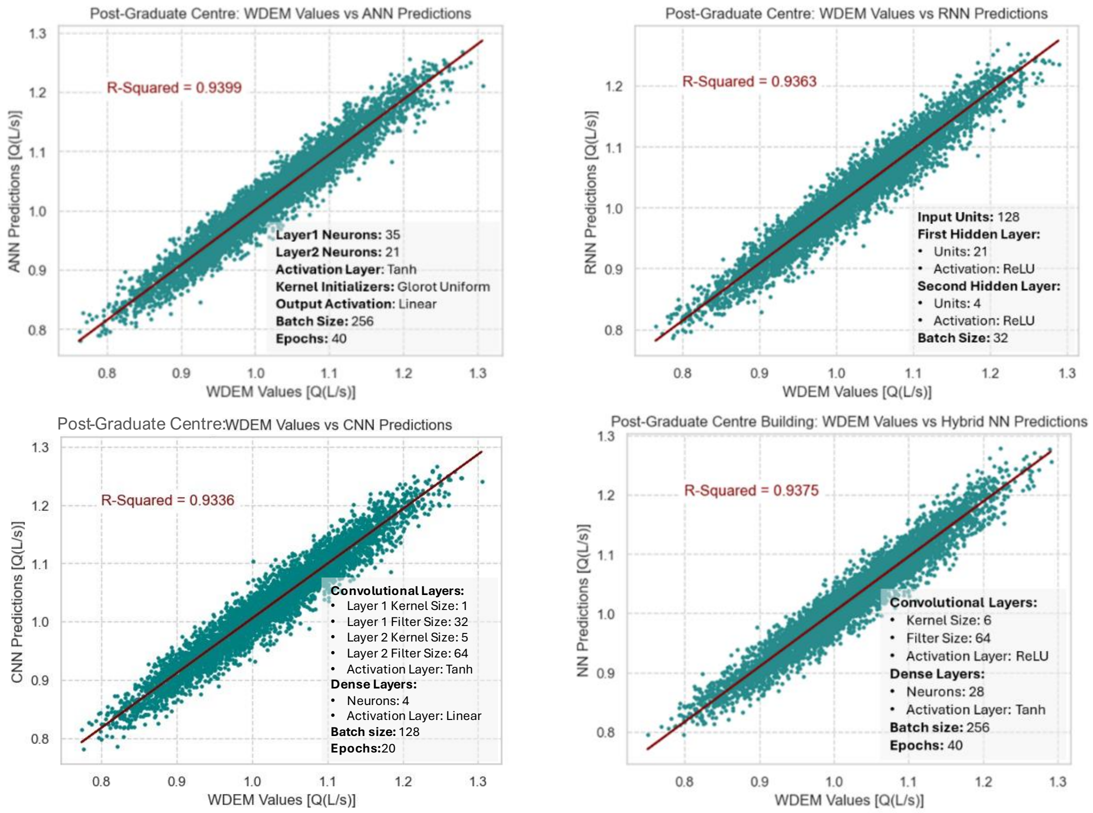

Figure 2 – WDEM-based model results for Post-Graduate Centre

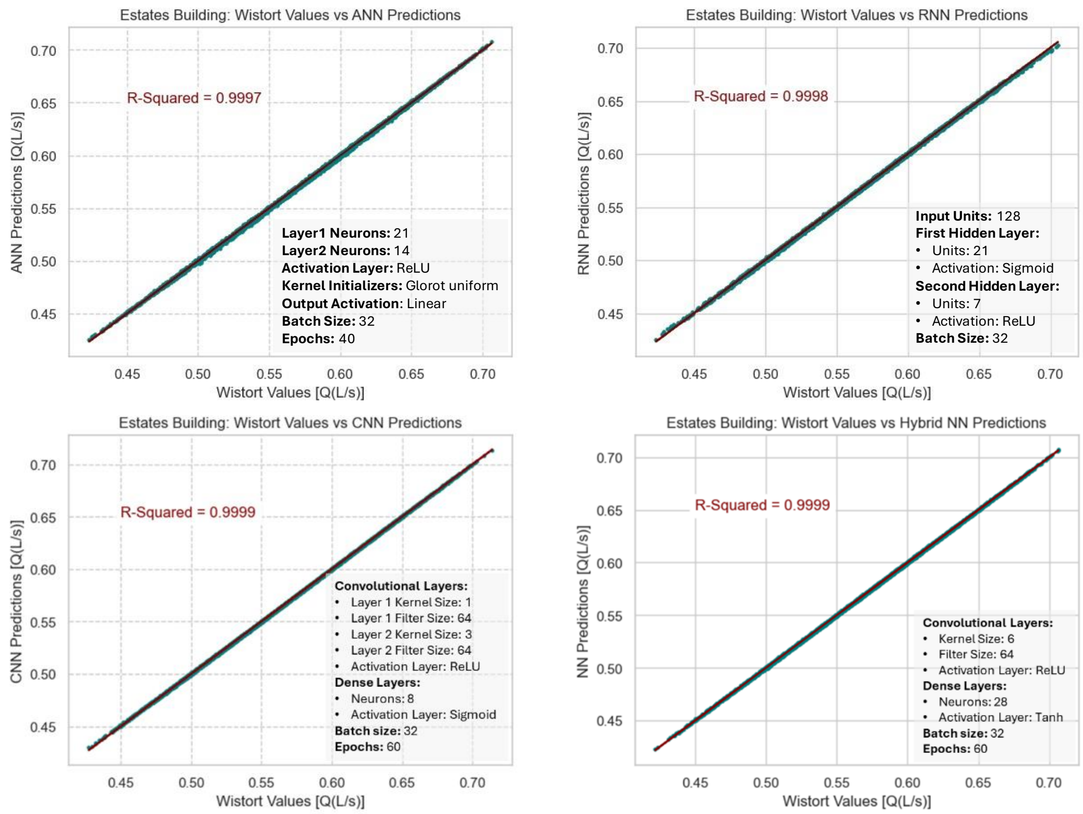

Figure 3 - Wistort-based model results for Estates Building

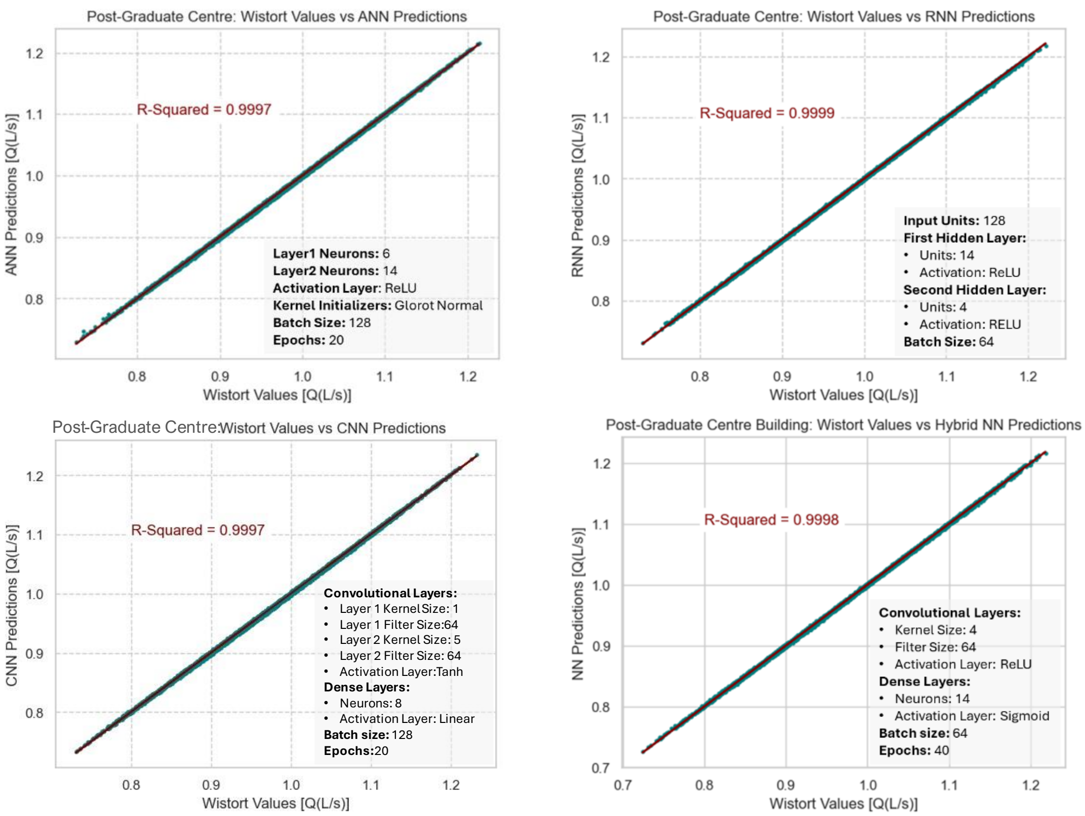

Figure 4 – Wistort-based model results for Post-Graduate Centre

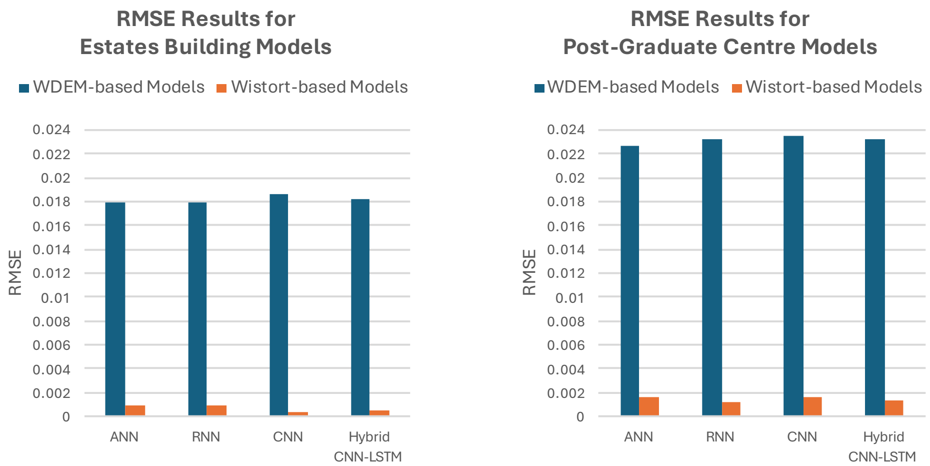

Figure 5 – RMSE Results

While the R-Squared metric is a measure of how well the data fits the model, it does not indicate the accuracy. The Root Mean Squared Error (RMSE) for each model was computed to measure the accuracy, as shown in Figure 5. For the WDEM-based models, the RMSE values for the Post-Graduate Centre are higher than those for the Estates Building despite the R-squared values being better. This can be attributed to the higher average Q values of the Post-Graduate Centre compared to the Estates Building. The RNN model in the Estates Building also generated the lowest RMSE, despite the R-squared of the ANN being better. The results for the Post-Graduate Building were more consistent, with ANN generating the best R-squared and RMSE values. Looking at both the R-Squared and RMSE values, the ANNs for the WDEM-based models of both the Estates Building and Post-Graduate Centre were chosen as the best computer models for estimating the SPWF using fixture use probability values. Both ANN models have two hidden layers, with 35 and 21 hidden neurons for the first and second hidden layers, respectively.

For the Wistort-based models, the RMSE values were generally lower than the WDEM-based models, not exceeding 0.002. This is expected given the good results based on the R-Square metric. The Hybrid CNN-LSTM models gave the lowest RMSE and were chosen as the best models as the R-Square values are very close to each other. The Hybrid CNN-LSTM has three hidden layers: Conv1D, LSTM, and the Flatten layer. The kernel size, filter size, LSTM units, and activation layers vary for each model.

As evident in Figure 6, the overestimation from the new neural network models were almost equal to the original models, proving the accuracy of the neural network models and the reduction of overestimation compared to the established standards.

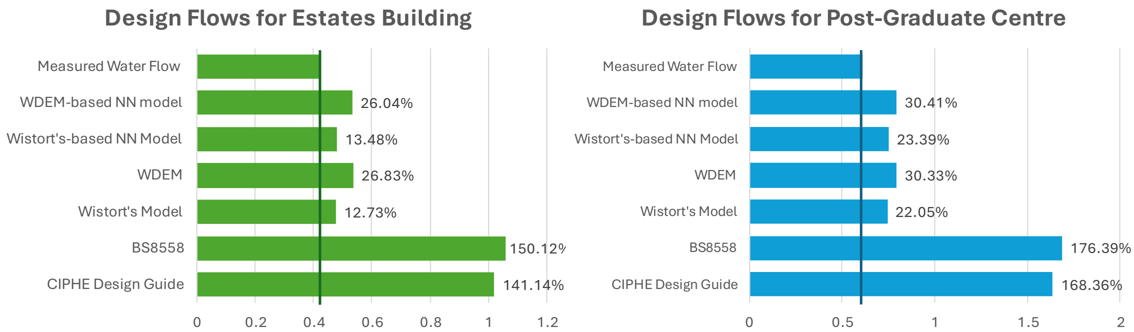

Figure 6 – Design Flows Comparison with Overestimation Percentage against Empirical 99th Percentile Values

5 Conclusion

This work focused on developing flexible neural network models to estimate the SPWF given only the probability values of fixtures, using the WDEM and Wistort's model. For both case study buildings, the ANN architecture produced the best estimations of the WDEM, indicating that neural networks can be used as computer models for stochastic-based methodologies. Meanwhile, the Hybrid CNN-LSTM architecture produced the best estimations for the Wistort's model.

An obstacle to address in this model development is ensuring cost-effectiveness, considering the significant time and computing resources required for implementing neural networks and optimization algorithms. Despite the underlying complexity of the modelling, the usage of this model remains straightforward for users, as it solely requires inputting water fixture information. Proving the viability of neural networks for SPWF estimation is beneficial for future studies and opens the path towards more data-driven methodologies to mitigate the overestimation problem in peak water demand estimation.

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Presentation of Author(s)

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