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Proceeding Paper

Application of Feedforward Artificial Neural Networks to Predict the Hydraulic State of a Water Distribution Network †

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Abstract: Improving the operational efficiency of water distribution networks (WDNs) is a subject that has been widely explored in the literature. Usually, a hydraulic model is used jointly with optimization methods, which require considerable computational effort, hindering real-time interventions. Surrogate models based on machine learning are being studied to estimate the hydraulic state of WDNs and reduce the processing time, and the results have been successful. In this paper, different feedforward artificial neural networks (FFNNs) of the multilayer perceptron (MPL) type were developed to estimate important hydraulic parameters that were applied to optimization algorithms, namely, (i) energy consumption; (ii) tank levels; (iii) pressure in consumption nodes; and (iv) minimum pressure. These parameters were chosen because they are frequently used in objective functions, minimizing energy consumption and leakage volume, as well in operational restrictions. The results showed that creating an individual MLP for each parameter can be a good strategy to improve MLP accuracy.

Keywords: artificial neural networks; optimization; water supply; machine learning

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1. Introduction

Water distribution networks (WDNs) have highly dynamic operations due to the consumption pattern of the systems. Therefore, real-time interventions are necessary to optimize their operations and guarantee service quality with minimal costs. This can be achieved by adjusting the pumps and valves. These adjustments are traditionally carried out using an optimization algorithm coupled with a hydraulic model to simulate the proposed changes and verify the technical feasibility of this approach [1]. Different parameters can be used to evaluate the proposed solution (leakage volume, energy consumption, water quality, resilience index, and pressure uniformity), and, according to the topology of the WDN, different operational restrictions can be set to verify the feasibility of the solution (maximum and minimum pressures, water level and tanks, and maximum number of switching pumps in the off position).

The literature shows that this approach of combining optimization algorithms with hydraulic models is capable of generating good results. However, for large and complex WDNs, the increase in computational effort hinders real-time interventions [2]. In many cases, it is possible to simplify the WDN model using a skeletonization process to (i) remove small pipes (in length or diameter); (ii) aggregate close nodes connected by short pipes; and (iii) replace pipes in series or parallel using an equivalent single pipe [3]. Although skeletonization can significantly reduce the computational effort, the results have an intrinsic error, especially when leakage is modelled as orifices.

An alternative approach to reduce these errors is to use data-driven methods based on machine learning. In this case, instead of using theoretical equations, the hydraulic behavior is expressed using observations made through measurements (flow, pressure, water level, and power). Indeed, the uncertainties of measurements are still a source of error. However, this surrogate model is less susceptible to uncertainties in the model topology. Artificial neural networks (ANNs) have been successfully used to solve different problems with WDNs [4]. However, the architecture of these ANNs needs to be carefully studied to apply them to real-time operations so that they can eventually replace hydraulic models.

Therefore, in this paper, the accuracy of an FFNN of the MLP type was evaluated for its application in the optimization process. Individual MLPs were created to estimate the most important parameters in an optimization procedure, namely, (i) energy consumption; (ii) tank levels; (iii) pressure in consumption nodes; and (iv) minimum pressure. The results showed that creating individual MLPs for each parameter can be a good strategy to improve the accuracy of the FFNN.

2. Methodology

2.1. Creating the Database

The Anytown WDN was used as a case study for this research. The network consists of 40 pipes, 19 nodes, two tanks, one reservoir, and one pump station. Using the MATLAB programming environment in conjunction with EPANET, code was developed in which four input parameters were set to the WDN operation: (i) consumption pattern; (ii) initial level for the two tanks; and (iii) pump rotational speed. Hourly hydraulic simulations were then carried out, and the following results were stored: (i) pump energy consumption; (ii) pressures at each node; (iii) minimum pressure; and (iv) final level of the two tanks. For each set of input parameters, the network produced a specific response. In this way, a loop was created to iterate over the range considered for the input parameters. Subsequently, the input parameters and their corresponding responses were stored in two separate matrices, one for the input data and the other for the WDN responses. A total of 58,212 scenarios were evaluated.

2.2. Development of the Artificial Neural Network

FFNNs of the MLP type were developed to solve the problems created by the complexity of the equations governing the operation of WDNs. In order to predict the four parameters of the WDNs (energy consumption, final pressures at the nodes, minimum pressure, and final tank levels), a specific MLP was created for each of these parameters. The architecture and training of each MLP was studied to provide the most accurate result. Thus, the number of hidden layers and neuros, the activation functions, and the training algorithm were set individually for each MLP. For all cases, the mean square error was used as the performance function, which is an adequate criterion for convergence. The data set was randomly divided into three different sets: 80% of the data were used to train the metamodels, 10% were reserved for validation, and the remaining 10% were used for testing.

After training the MLP, a hydraulic simulation was carried out over a 24 h period. Subsequently, the MLP was provided with the same initial parameters as those used in the hydraulic model, enabling a comparative assessment of the results.

3. Results

3.1. Energy Consumption Prediction

The MLP for the prediction of energy consumption was very accurate. Figure 1a shows great similarity between the actual values from the hydraulic simulation and the values predicted by the MLP every hour. Figure 1b shows the error between the real and predicted values of the MLP, together with the average error. The average error during the 24 h period was 1.6 W, and the largest error was 78 W (8.5%). The coefficient of determination, R2, was calculated, and the result was 0.9712.

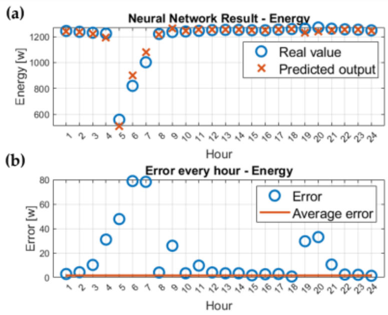

Figure 1. Results for energy consumption: (**a**) comparison between actual value and ANN prediction; (**b**) error and average error of the results.

3.2. Predicting Tank Levels

The MLP for the prediction of the tank levels showed very accurate results, especially for tank 2. Figure 2a,c show the comparison between the actual value from the hydraulic simulation and the neural network prediction for tanks 1 and 2, respectively. Figure 2b,d show the error between the actual and predicted values, as well as the average error. The average errors were 0.08 m for tank 1 and 0.005 m for tank 2, and the largest errors were 0.64 m (0.6%) for tank 1 and 0.47 m (0.4%) for tank 2. The coefficient of determination was 0.9976 for tank 1 and 0.9977 for tank 2.

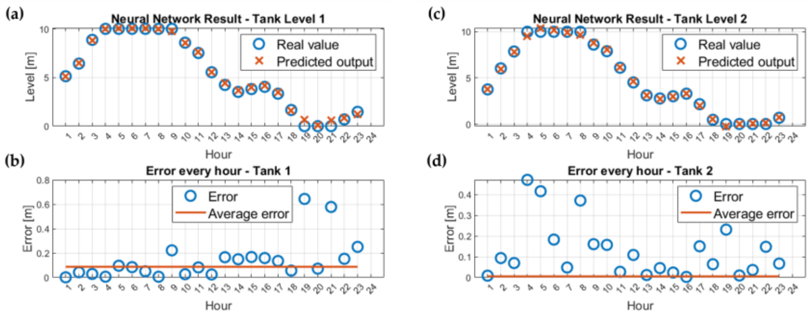

Figure 2. Results for tank levels: (**a**,**c**) comparison between actual value and ANN prediction; (**b**,**d**) error and average error of the results.

3.3. Prediction of Node Pressures and Minimum Pressure

The MLP's predictions for node pressures were consistent. The MLP was able to efficiently represent the variation in pressures, with some deviations from the observed values. Figure 3 shows the results for nodes 14 and 1, which respectively represent the nodes with the best and worst performance in terms of mean absolute error.

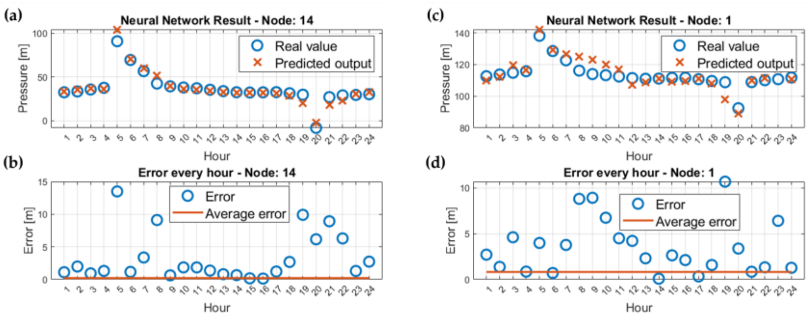

Figure 3. Results for pressures at nodes 14 and 1: (**a**,**c**) comparison between actual value and ANN prediction; (**b**,**d**) error and average error of the results.

Figure 3a,b show the comparative results of the hydraulic simulation and the MLP prediction, and Figure 3c,d show the error between the actual and predicted values at each hour, as well as the average error. On average, the mean absolute error was 0.20 m for node 14 and 0.81 m for node 1, and the largest deviation observed was 13.5 m (12%) for node 14 and 10.7 m (11%) for node 1. Although some specific deviations with percentages above 10% were identified, the overall average of the errors remained low. Thus, the MLP is considered reliable enough to be used as an operational tool. The lowest pressure recorded in the WDN, as calculated by the hydraulic simulation, reached −8 m at node 19 at 8 pm. The MLP predicted the minimum pressure in the same node at the same time, but with a value of −2 m.

4. Conclusions

The application of FFNNs of the MLP type in this study aimed to create metamodels capable of predicting the operational state of a WDN over a 24 h period. The results were effective overall, with only minor variations at specific points. The average error observed between the predicted and actual values for energy consumption and tank levels was so low that it can be considered almost negligible. Although the prediction of pressures at the nodes showed some specific deviations from the actual values, the average error still indicates a satisfactory ability of the MLP to predict pressures. In addition, the MLP was able to accurately determine both the time and the node where the pressure would be at a minimum, with minimal deviation from the actual value, once again demonstrating its good performance and its usefulness in practical applications for monitoring and controlling WDNs.

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