A Proactive Approach for the Sustainable Management of Water Distribution Systems

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Abstract: Today, water distribution systems need to supply water to consumers in a sustainable way. This is connected to the concept of Watergy, which means the satisfaction of user demand with the least possible use of water and energy resources. Thanks to modern technologies, the forecasting of water and energy demand can help achieve this goal. In particular, water demand forecasting allows water distribution companies to know in advance how water resources will be allocated, it can help identify any anomalies in water consumption, and it is essential for pumps scheduling. On the other hand, energy consumption forecasting has other important roles, such as energy optimization, identification of anomalous consumption, and planning of energy load. The present paper aims to develop short-term water demand and energy forecasting models through innovative machine learning-based methodologies for the water distribution sector: global forecasting models, the N-Beats machine learning algorithm, and transfer learning approaches. These tools demonstrated very good performances in the creation of the models previously mentioned.

1 INTRODUCTION

Today water distribution systems (WDSs) are responsible for water delivery with the required quality, pressure, and quantity, but with the lowest possible water and energy waste (Adedeji et al., 2022), (Mesalie et al., 2021). This goal is linked to the concept of Watergy efficiency, which means the satisfaction of user demand with the least possible use of water and energy resources (Bolognesi et al., 2014).

Water scarcity poses a great threat to humans. It is predicted that by 2025, 1.8 billion people may face severe water shortages, and about two-thirds of the world's population could be experiencing water stress (Hans et al., 2014). This scenario of decreasing water availability is the result of the amplification of various factors, such as climate change, population growth, increased urbanization rates, and industrial development (Patil et al., 2022), (Leitão et al., 2019), (de Souza Groppo et al., 2019), (Esen et al., 2020). These phenomena have caused a significant increase in water consumption reducing the available water resources (Hussain et al., 2022), (Stańczyk et al., 2022). Indeed, the increase in water consumption is not accompanied by an increase in water resources.

Water demand forecasting can help in identifying wasteful behavior or leakages in the system, which lead not only to higher water consumptions but also to higher energy consumption (Kofinas et al., 2016). Furthermore, water demand forecasting prevents energy waste through the possibility of pumps scheduling, as it will be pointed out in the next section.

Indeed, concerning energy consumption, a water distribution system incurs high energy costs in all of its operations (water extraction, treatment, and distribution), but pumping systems are the biggest cause of consumption (Sarmas et al., 2022). Luckily, the optimal management of pumps' operations, called

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pump scheduling can be a source of savings (Gan et al., 2022). This concept would be better explained if the Figure 1 has been considered.

Figure 1 is a simplified representation of how the water is distributed to final users in a water distribution network. In this network, each zone is served by a pump system composed of 3 collaborating pumps (parallel pumps) that distribute water collected in a reservoir. After each pump system, there is a single pipe in which the water flows to a network zone. Parallel pump systems give space for energy savings opportunities because it can be decided when to turn on/off pumps based on the water demand and energy consumption (Gan et al., 2022). In other words, not all pumps need to operate always simultaneously, for example during the night when the water demand is usually lower concerning working hours.

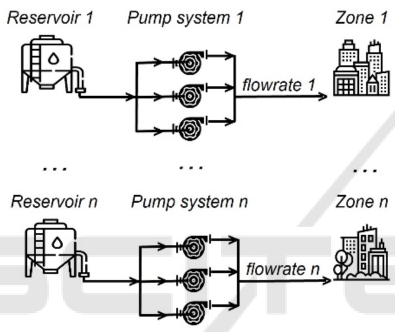

Figure 1: A simple representation of a WDS.

In this context, forecasting the aggregated water demand of each network zone plays a very important role to schedule pumps' operations. Accurate forecasting helps in deciding how many and which pumps to turn on at a given moment of the day based on water demand. Furthermore, forecasting the energy consumption of pump systems can also be useful for different purposes: energy optimization, identification of anomalous consumption, and planning of energy load (Yi et al., 2022), (Alhendi et al., 2022). In particular, the planning of the energy load to be supported is fundamental to predicting the necessary costs to be incurred and also if the system will be able to cope with the required power.

In conclusion, today Watergy efficiency is the main goal that water distribution companies want to achieve and the digitalization that has pervaded the management of water resources permits them to get as close as possible to this goal. Indeed, the sustainability of the water supply system would not be possible without the industrial revolution of the water sector, called Water 4.0 (Adedeji et al., 2022). Automation, increased integration of sensors, Internet of Things, big data analysis, and artificial intelligence are some of the features of Water 4.0. In particular, the most famous applications of artificial intelligence in the management of water supply systems are anomaly detection and water demand forecasting (Adedeji et al., 2022). The present paper is focused on the latter, together with the pumps' energy consumption forecasting. In particular, it is implemented a 24-h horizon forecasting with a timestep of 1 hour.

The proposal presented in the paper has been developed inside a research project funded by "Italian Ministry of Enterprises and Made in Italy" (https://www.mimit.gov.it/en/); details about the research project are given in the Acknowledgment section. One of the partners of the project, EHT, is an enterprise involved in the digital transformation of water distribution systems. The goals of the research here presented were specified by this enterprise together with sponsors of the project, fully involved in the same business area. Moreover, the enterprises involved in the project evaluated the results achieved in order to understand to what extent these results could be valuable in practical terms; the evaluation of these results was successful as the impact of the proposal on the real management of water distribution systems was considered important.

The paper is organized as it follows. In Section 2 the authors introduce related studies about machine learning (ML) models used for water demand forecasting and pumps energy forecasting. In Section 3 the authors describe the proposed approach to solve the previously cited forecasting problems, explaining how the dataset was simulated, the preprocessing steps were done before the machine learning algorithm, the proposed forecasting models, and finally, the performance metrics used to evaluate models. In Section 4 and Section 5 the obtained results and conclusions with future works, respectively, are reported.

2 RELATED WORKS

Water demand forecasting was addressed with different machine learning forecasting models in the literature. In (Niknam et al., 2022) and (de Souza Groppo et al., 2019), a detailed review of the methods employed, and important future challenges are given.

In particular, the three most used methods are in order: traditional time series (e.g., autoregressive integrated moving averages, exponential smoothing), different types of artificial neural networks (e.g., long short-term memory, radial basis function ANN, gated recurrent units), support vector machines.

Time series models are not able to reach high accuracy forecasts as machine learning models, because they are not able to learn complex, non-linear patterns in demand forecasting. Despite this, they are among the most used models due to their ease of use and interpretation (Niknam et al., 2022). Among the most recent papers, AutoRegressive Integrated Moving Averages (ARIMA) and Exponential Smoothing (ES) are the most used time series models. In (Ebrahim Banihabib et al., 2019), two forecasting methods for daily urban water consumption forecasting are used; one of them is ARIMA. In (Karamaziotis et al., 2020) different methods, among which ARIMA and ES, are used to realize a mid-term forecast. In (Ristow et al., 2021) the ARIMA and ES methods are used to forecast monthly urban water demand.

Regarding ANN, in (Salloom et al., 2021) an hourly water demand forecasting with the Gated Recurrent Unit (GRU) method is presented. In (Hu et al., 2021), the GRU method is also used, but with the aim to make an hourly water demand forecasting, demonstrating the superiority of this method compared to Support Vector Machines (SVM).

About the SVM method, in (Shabani et al., 2017), it is used with a polynomial kernel function to predict monthly water demand. In the paper (Candelieri et al., 2019), the authors used the SVR with a parallel global optimization tuning of hyperparameters, which allowed them to increase the accuracy of the short-term forecast.

The pumps' energy consumption forecasting of a water distribution system is instead a less explored area of study. In (Yi et al., 2022), the authors used four algorithms (multiple linear regression, random forest, deep neural network, and support vector regression) to forecast the energy consumption of an entire water system and the three subsystems of conveyance, treatment, and distribution. They pointed out the lack of similar papers.

Partly according to the research carried out, and partly also according to what was affirmed by (Niknam et al., 2022), there are some quite unexplored topics in literature.

In water distribution systems usually, water demand time series are forecasted individually, meaning that one model for each time series is developed. Instead, global models could allow the creation of a single model for all the time series (Montero-Manso et al., 2021). This is essential considering that, over the years, thanks to the technologies available, the number of available series will always increase, and new tools are needed to manage it.

Furthermore, global models, learning from multiple time series simultaneously, allow the use of transfer learning approaches (Bandara et al., 2021). If the model is trained on fairly heterogeneous series, transfer learning should allow forecasting on series never seen before.

Finally, to the best of the authors' knowledge, among all the algorithms used, there is one that has never been used in water demand and pumps' energy consumption forecasting of an entire water distribution system: N-Beats (Oreshkin et al., 2020). This is an algorithm developed specifically for time series.

In summary, this paper aims to fill the gaps in the literature by developing short-term water demand and pumps' energy consumption forecasting models through global models using the N-Beats algorithm and transfer learning approach.

3 DESCRIPTION OF THE APPROACH

In this section, the authors describe the tools used for data simulation, the dataset preprocessing phases, the proposed forecasting method, and the performance metrics for the models' evaluation.

3.1 Data Simulation

Data plays a strategic role in a machine learning approach, as known. Considering the problem presented in this paper, information about the WDS like pipes flowrate and pumps' energy consumption, is strongly required. Data for water distribution systems are often not available or of poor quality (Maira et al., 2014). As the main aim of the paper was the feasibility study of the proposed approach, data needed to run the machine learning-based solution was synthetically generated.

Data were simulated through Water Network Tool for Resilience (WNTR), a Python package based upon EPANET software, designed for the simulation of water distribution networks (WDNs), version 0.5.0 (Klise et al., 2020). The WNTR simulator takes as input an .inp file containing the network characteristics (e.g., pipes, pumps, valves, junctions, tanks, reservoirs, water demand patterns, pumps curves) and it returns different time series with the simulation results (e.g., pipes flowrate, nodes pressure, pumps' energy consumption).

The network used for the simulation is a simplified version of the WDN of the city of Milano (Italy); it is made up of 12,354 nodes, 17,548 links, 128 patterns, and 95 pump curves (one for each pump). At each node representing a user, a water demand pattern has been assigned. The demand pattern was extrapolated from water consumption data collected every minute on particular dates. More in-depth, these consumption data were aggregated in a dataset, where each column represented a specific zone, and each row was the water consumption of a particular minute of the day. In order to extract coefficients of the general demand pattern, a column with the total consumption per minute was added. Finally, the column with the coefficients per minute was obtained by dividing each observation of the total consumption column by the average value of this column. Then, the pattern was aggregated with the mean operator to obtain 1-hour interval observations, useful for the subsequent step of the hourly forecasting. True patterns of 24 hours are represented by a black line in Figure 2.

From this real demand pattern, other 4 patterns were obtained adding for each value of the true one a random noise. In order to create a similar but different pattern, at each value of the true pattern was added a quantity that randomly increased or decreased the original value. To calculate this quantity, first of all, a random noise between -1.5 and 1.5 was generated by multiplying a random value between 0 and 1 by 3 and subtracting 1.5. Then, this value was multiplied by 0.05 to obtain a relative number between the 5% of -1.5 and 1.5. For each value of the real pattern, this process was repeated 4 times to obtain other 4 similar patterns. Synthetic patterns of 24 hours are represented in Figure 2 and compared with the true values.

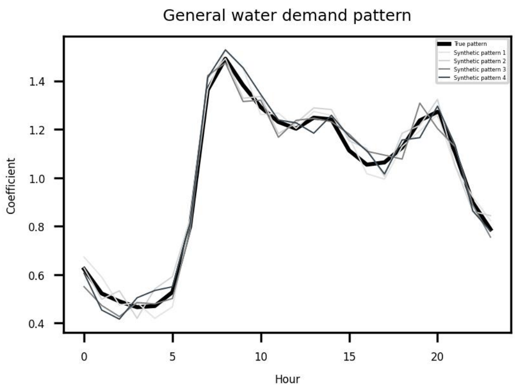

Figure 2: True water demand pattern and synthetic ones.

Even if this is the general water demand pattern, in the network.inp file each node demanding water has a specific base demand. This different base demand for each node makes the demand pattern of each node in the network unique.

Furthermore, the pump's speed was set constant because WNTR at the moment doesn't support variable speed pumps.

The water distribution was simulated using this network to obtain 5 days of hourly time series (120 observations). The simulation was a demand-driven simulation, meaning that the pressure in the system depends on the node demands, and that node demands are always satisfied (Klise et al., 2020). The time series collected to proceed with the analysis are: flowrates series for each pipe (120 rows, 17548 columns), and energy consumption of each pump (120 rows, 95 columns).

Table 1 and Table 2 provide an example of flowrates and energy consumptions datasets, respectively, where f indicates the flowrate and e is the energy, while the index of the rows represents the hours (120 of total hours because there are 5-day hourly data).

Table 1: Simulated flowrates time series example.

	Flow pipe id 1	Flow pipe id 2	…	Flow pipe id 17548
1	$f_{1,1}$	$f_{1,2}$	…	$f_{1,17548}$
2	$f_{2,1}$	$f_{2,2}$	…	$f_{2,17548}$
…	…	…	…	…
120	$f_{120,1}$	$f_{120,2}$	…	$f_{120,17548}$

Table 2: Simulated energy consumptions time series example.

	Energy pump id 1	Energy pump id 2	…	Energy pump id 95
1	$e_{1,1}$	$e_{1,2}$	…	$e_{1,95}$
2	$e_{2,1}$	$e_{2,2}$	…	$e_{2,95}$
…	…	…	…	…
120	$e_{120,1}$	$e_{120,2}$	…	$e_{120,95}$

3.2 Feature Selection

A feature selection procedure was done for both flowrates dataset and pumps' energy consumption dataset to obtain the best input setting for the machine learning algorithms.

As represented by Figure 1, after each group of pumps there is a pipe from which water flows to a zone based on the zone's aggregate water demand. After this pipe, there would be many other pipes that allow water to reach all the end users. Since the authors were interested only in the aggregated demand of a network area, for each served zone, the pipe represented in Figure 1 was selected through its id, and the flowrates dataset was reduced from 17,548 to 27 columns (one pipe for each network zone). Among the 27 time series, 7 of them showed an almost constant pattern, and consequently, they were excluded from the analysis. Therefore, a further reduction was implemented from 27 to 20 columns because the pipes of areas having an almost constant simulated daily pattern were excluded.

The names of the selected zones of the Milano network are: Anfossi, Armi, Assiano, Baggio, Cantore, Chiusabella, Cimabue, Comasina, Crescenzago, Feltre, Gorla, Italia, Lambro, Novara, Padova, S. Siro, Salemi, Suzzani nord, Suzzani sud, Vialba.

The final dataset was composed of 20 time series, each one representing the 5-day aggregated water demand of a network zone with an hourly interval.

The pumps' energy consumption dataset needed a first reduction of features to contain only the pumps' energy consumption of the previously selected network's zones (from 95 to 72 pumps). Thus, a file associating each pump with its area was consulted to make the above selection. In each area, the pumps collaborate for the delivery of water to the specific zone. The number of collaborating pumps for each area ranges from a minimum of 2 to a maximum of 5. Furthermore, the consumption of pumps in the same zone was aggregated with the sum operator to prepare the dataset for the pumps' energy consumption forecasting of a network zone.

The final dataset was composed of 20 time series, each one representing the 5-day aggregated pumps' energy consumption of a network zone with an hourly interval.

3.3 Model Definition

The aim of the paper is to develop machine learning (ML) models for the aggregated water demand and pumps' energy consumption forecasting of 20 different water distribution network zones.

Each time series was normalized with the Min-Max scaling so that the range of each variable becomes 0-1. More specifically, given max the maximum value of a variable, and min its minimum value, each observation x is transformed according to this formula:

$$\frac{x - min}{max - min} \tag{1}$$

Then, to prepare the datasets for the machine learning algorithms, each time series was divided into a training set (first 4 days, 96 hours of observations) and a test set (last day, 24 hours of observations).

The proposed forecasting approach is shown below in Figure 3 and Figure 4.

All machine learning models were performed through Darts (version 0.23.1), a Python machine learning library specific for time series analysis, in particular for time series forecasting (Herzen et al., 2022). The powerful feature of Darts is to provide modern machine learning functionalities with a user-friendly and easy-to-use API design (Herzen et al., 2022). Furthermore, all deep learning forecasting models implemented in Darts are global forecasting models. A global forecasting model has great potential because it can be trained with multiple time series and it can make forecasting not only for these time series but also for unseen series (transfer learning approach).

Other important information about the training of global forecasting models will be provided in the next paragraph, together with detailed information on the architecture of the used model.

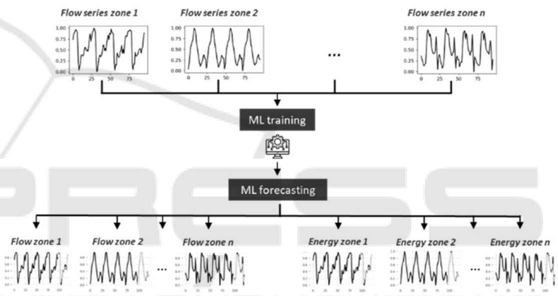

Figure 3: Water demand and pumps' energy consumption forecasting through a unique ML model trained with flowrates series.

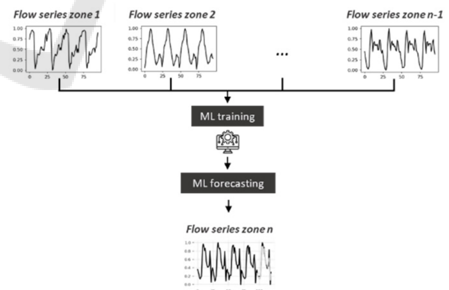

Figure 4: Water demand forecasting for one zone through a ML model trained with all the flowrates series excluding the forecasted one.

As depicted by Figure 3 and Figure 4, the water demand forecasting of each flowrate time series was addressed with two different methodologies.

The first consists in the creation of a global forecasting model taking as input all the flowrates series training sets, and giving 24 hours of forecast for all of these series (Figure 3). The Darts model used for forecasting is the N-Beats model. The default hyperparameters were maintained except for two of them: the input_chunk_length and the output_chunk_length. The former specifies the length of the time series portion taken in input by the internal neural network and was set to 72, meaning that the neural network looks 72 hours in the past. The latter represents the length of the forecast of the model and was set to 24, meaning that the neural network produces 24 points of forecast.

The second method consists in the creation of a global forecasting model for each flowrate series taking as input all the flowrates series training sets except for this one, and giving 24 hours of forecast for this series. This approach exploits the knowledge gained with the training of some series to forecast unseen series (transfer learning). Figure 4 represents an example of this method applied for the forecasting of a single flowrate series.

The latter method was applied also for the construction of the pumps' energy consumption forecasting model. The energy consumption of pumps strictly depends on the flowrate pattern. The WNTR simulator calculates it considering the pump flowrate, the node head, and the global efficiency of the pump (set to 75%). Therefore, each pump's energy consumption time series has almost the same pattern as the flowrate time series in the same network zone. Instead of creating an additional model, the first global model trained with all the flowrates time series was tested for the energy consumption forecasting of each zone (see Figure 3).

3.4 N-Beats Global Forecasting Model

This section provides insights into the used model (N-Beats) and how the training of global models works on the Darts library.

Recently, the authors of (Oreshkin et al., 2020) proposed a neural network architecture designed for time series forecasting called N-Beats (Neural basis expansion analysis for interpretable time series forecasting). In the following, the architecture of the model will be described, as shown in Figure 5; more details may be achieved by (Oreshkin et al., 2020).

Given a forecast horizon (or forecast period) of length H and an observed series history (or lookback period) of length T (where $T = n \times H$), the model takes as input the lookback period to learn the behavior of the time series, and it predicts the behavior of the same time series in the forecast period (upper part of Figure 5). There are different stacks (right part of Figure 5), and at the end, the output of each stack is combined to obtain a global forecasting output. In each stack, there are multiple blocks (middle part of Figure 5), and each block has a fully connected stack with 4 layers that do both forecasting and backcasting (left part of Figure 5). The difference between forecasting and backcasting is the direction of predictions: the former predicts future values by looking back at historical data, and the latter extrapolate past values from future data (forecasting backward in time). Furthermore, nonlinearities are provided by the ReLU activation function. Activation functions have an important task because they introduce non-linearities in the network. In other words, learning complex pattern in the data, help in the resolution of real-world problems. There are different activation functions that can be used in the network, but the ReLU (rectified linear unit) is the most popular because it is simple and fast (Nair et al., 2010).

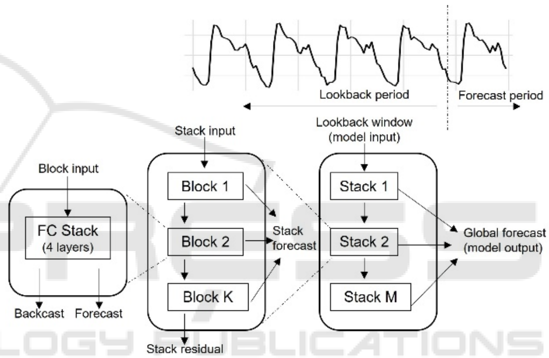

Figure 5: N-Beats architecture.

This model has been used through the Darts Python library. Darts library has implemented many forecasting models, but only a subset of them can be trained with multiple time series (among which N-Beats). These models are called global forecasting models. Time series can be divided into two classes: target time series (series to be forecasted) and covariate time series (series not to be forecasted but to be taken into consideration to help target time series forecasting). The present paper does not consider the presence of covariates, therefore models take in input only target series. This choice lies in the fact that water demand history is the main factor influencing future demand, therefore it is sufficient for developing accurate models (Hu et al., 2021), (Bakker et al., 2013).

When a model with multiple target time series needs to be trained (as in our case), Darts creates a dataset aggregating multiple input/output pairs from the provided time series. The length of the input is equal to the input_chunk_length hyperparameter, while the length of the output depends on the output_chunk_length hyperparameter.

Figure 6 shows the training phase of a model with two example series of different lengths and different time stamps in input.

In this example, the input_chunk_length is equal to 4, while the output_chunk_length is equal to 2. The number of samples used for training is calculated by subtracting from the time series length the sum of the input_chunk_length and output_chunk_length, and adding 1 to this result. Therefore, the first series has a number of samples used for training equal to 9, while the number of samples of the second series is 7. A training epoch in multiple series models consists of the complete pass over all the samples of all the series. Finally, the most important things to point out are that series do not need to have the same length, the same time stamps, or the same frequency (although this is not our case).

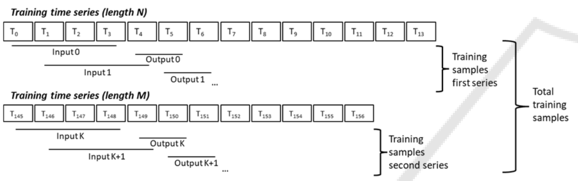

Figure 6: Training of global models in Darts library.

3.5 Performance Metrics

Different metrics were considered for the performance evaluation of forecasting models: mean absolute error (MAE), symmetric mean absolute percentage error (SMAPE), mean squared error (MSE), and root mean square error (RMSE).

MAE is a measure of error between predicted and true values, and it is calculated as an arithmetic average of the absolute errors (Hyndman et al., 2006).

SMAPE is a measure of accuracy based on relative errors, therefore it is a percentage value (Hyndman et al., 2006), (Bandara et al., 2021).

MSE is a measure indicating the average squared difference between predicted values and actual values (Hyndman et al., 2006).

RMSE is calculated as the square root of the mean of the square of all the errors (Hyndman et al., 2006).

For all of these measures, the lower the values, the better the model performance.

4 RESULTS

In this work, innovative machine-learning based methodologies are proposed to develop short-term water demand and energy forecasting models. This important task was addressed with the use of global forecasting models and transfer learning approaches.

First of all, four different global models were tested to select the one that provided the most accurate water demand forecasting. Among the models available within the Darts python library, the ones that were tested are: N-Beats, RNN, BlockRNN, and Transformer.

Performance metrics are reported in Table 3.

Table 3: Performance metrics of N-Beats, RNN, BlockRNN, and Transformer global models.

	N-Beats	RNN	Block RNN	Transf
MAE	0.031	0.188	0.23	0.16
SMAPE	21.322	52.15	56.174	45.762
MSE	0.003	0.06	0.075	0.043
RMSE	0.043	0.237	0.265	0.194

Among the models used, the N-Beats model outperforms the others according to all metrics considered, confirming its superiority in terms of forecasting accuracy. The other algorithms obtained very similar metrics' results, and the following ranking was obtained in decreasing order of performance: N-Beats, Transformer, RNN, BlockRNN. Taking as an example the SMAPE metric, it can be seen that considering the N-Beats model this metric is reduced by more than half compared to all the other models. The outperformance of this model may be attributed to its ability to do both backcasting and forecasting, which is a property that greatly differentiates it from the other algorithms, as said before in Section 3.4 while describing its architecture.

The performance metrics of the N-Beats global forecasting model (Table 3, first column) have been compared to the ones obtained from the creation of single models trained with one series at a time; in this case, the following values have been achieved: MAE=0.030, SMAPE=21.839, MSE=0.003, RMSE= 0.043. As it can be easily pointed out, almost identical results have been achieved. This situation may have been arisen because a restricted amount of data was used, but building a global forecasting model trained with a lot of real data with a longer period of time may benefit from learning from more patterns at the same time. Indeed, related time series could improve the overall predictions with respect to the result obtained with a collection of local models (Hewamalage et al., 2022). However, the time spent for training one model with multiple time series was lower than the total time needed to train a model for each series (36 seconds and 476 seconds respectively). This could be justified considering that the model complexity of local models grows proportionally to the number of time series in the dataset, and it can be higher than the constant complexity of the global model (Hewamalage et al., 2022). As said in Section 1, in the Water 4.0 era, water distribution systems are characterized by increased integration of sensors, Internet of Things, and big data. As a result, so much more data can be collected, analyzed, and exploited in the decision-making and planning phases. However, having access to all this information also means learning how to manage it properly. The results obtained demonstrate that the use of global models meets these needs, as forecasting can be performed by training a single model on multiple series with less time spent than creating multiple local models.

Pumps energy consumption patterns strictly depends on the water demand of the respective zone. For this reason, the previously created model trained with water demand time series has been used to reach the goal of pumps' energy consumption forecasting. Performance metrics results demonstrate the effectiveness of the approach (MAE: 0.032; SMAPE: 21.305; MSE: 0.003; RMSE: 0.043).

Finally, it has been explored the capacity of global forecasting models to forecast previously unseen series. For each flowrate time series, it has been created a model trained with all the other series and tested with this excluded one. Out of 20 forecasts, 18 of them produce very good results, demonstrating the ability of the models to generalize well (MAE: 0.079; SMAPE: 25.141; MSE: 0.012; RMSE: 0.1), while the other two have been considered unacceptable forecasting (MAE: 0.203; SMAPE: 97.746; MSE: 0.057; RMSE: 0.238). The worst performance of transfer learning in this small group of time series may be attributed to the fact that the patterns of these time series are too different from the group of time series on which the model is trained. Consequently, the fact that these two series have a totally different pattern from the others suggests that a global model made up of as heterogeneous series as possible can obtain better performances in the case of transfer learning.

A few examples of comparisons between the forecasting of global forecasting models and transfer learning models are reported in Figure 7, Figure 8, and Figure 9.

In conclusion, an essential step in the water and energy forecasting approach is to compare the results of this study with similar research in the past literature. However, no comparative research was found as the use of global models, the N-Beats algorithm, and transfer learning techniques is a field being explored for the first time in the water distribution sector.

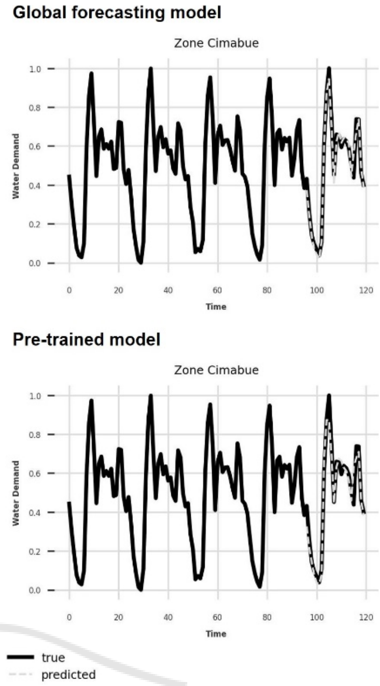

Figure 7: Water demand forecasting for the zone named Cimabue with the global forecasting model and the pre-trained model.

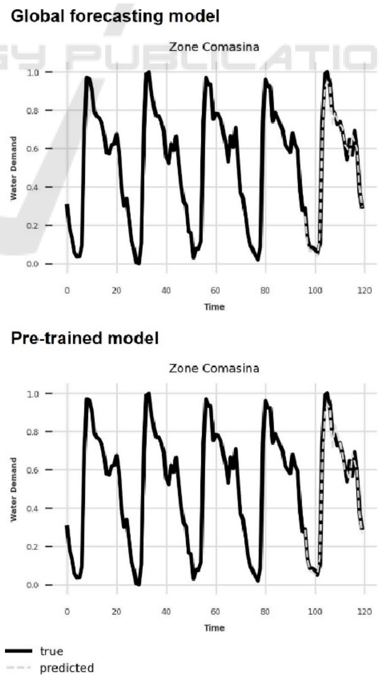

Figure 8: Water demand forecasting for the zone named Comasina with the global forecasting model and the pre-trained model.

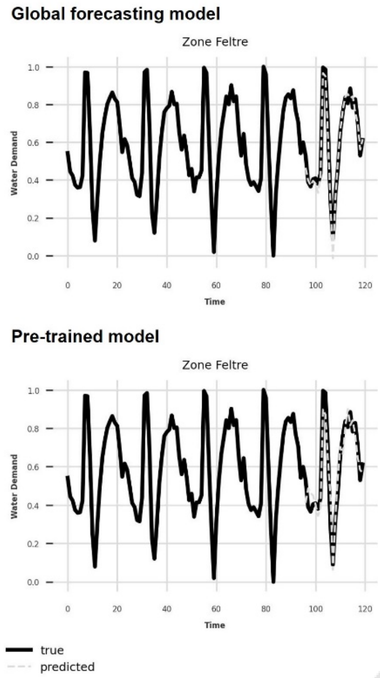

Figure 9: Water demand forecasting for the zone named Feltre with the global forecasting model and the pre-trained model.

5 CONCLUSIONS

In this study, the authors developed a short-term water demand and pumps' energy consumption forecasting with simulated data from the Milano water distribution network. In particular, hourly data were used to make 24-h horizon forecasts.

To the best of the authors' knowledge, the approaches proposed for forecasting differ from previously published studies in different points.

First of all, both water and energy forecasts are investigated together for the same water distribution network.

Then, it is the first time that global models are used in the water sector, and this has made it possible to create fast a single and general model able to generalize on unseen time series (transfer learning).

Finally, although N-Beats was never used before in the water demand and pumps' energy consumption forecasting of an entire water distribution system, the results achieved by the authors pointed out that it offered the best performance; on account of these results, it seems very suitable to be used in this field.

Future studies plan to test this methodology with real data covering a longer period, to create more complex models able to detect weekdays, weekends, and yearly patterns, or trends if present. Furthermore, also mid-term and long-term forecasts could be developed.

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