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RESEARCH PAPER

Developing a Vertical Federated Machine Learning Framework for Predicting Energy Consumption in Wastewater Treatment Plants: A Case Study of Melbourne

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Abstract

This study presents a Vertical Federated Machine Learning (VFed-ML) framework designed to predict energy consumption in wastewater treatment plants (WWTPs) using actual data from a Melbourne-based facility. The effectiveness of various machine learning models including regression, ensemble learning, decision trees, and artificial neural networks were assessed for energy consumption prediction. Feature selection techniques using XGBoost and Random Forest were conducted to identify key variables that improve model performance. The proposed VFed-ML framework enables multiple agencies to collaboratively develop a unified machine learning model while ensuring the secure and efficient integration of multi-source data. The performance of the federated model was assessed over successive training rounds by analyzing the convergence of training and validation loss curves. Overall, the progressive decline in loss values during the later training rounds indicates that the model is effectively learning and improving its performance over time. The final model demonstrated improved predictive accuracy with minimal signs of overfitting, highlighting its ability to generalize well. These findings suggest that the proposed approach can be adapted to other WWTPs by incorporating plant-specific data. Key challenges such as data heterogeneity, communication bottlenecks, and model convergence, were identified and recommendations to address these issues were provided. The study also outlines opportunities for future research, including the incorporation of additional variables related to operational and external factors. In conclusion, the VFed-ML framework offers a promising solution for optimizing energy consumption predictions in WWTPs, safeguarding data privacy and security. Its flexibility allows for customization to other plants, highlighting its potential for real-world applications in environmental monitoring and resource management.

Highlights

The study develops a Vertical Federated Machine Learning (VFed-ML) framework that securely integrates multi-source data for predicting energy consumption in wastewater treatment plants (WWTPs) while maintaining data privacy.
The VFed-ML framework utilizes efficient hyperparameter tuning, custom evaluation, and aggregation strategies (FedAvg), ensuring high model accuracy and generalization without centralizing sensitive data.
The proposed methodology is scalable across different WWTPs, allowing for plant-specific data integration and enabling more accurate, customized energy consumption predictions and treatment optimizations.

Keywords Federated machine learning · Wastewater treatment plants · Energy consumption · Artificial neural networks

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Introduction

With the ongoing social and economic developments worldwide, there has been a corresponding increase in wastewater production, placing significant strain on wastewater treatment plants (WWTPs). These plants are responsible for the purification and treatment of wastewater before it is released into the natural environment. The treated water from WWTPs presents a valuable opportunity to address water scarcity issues, as it can be repurposed for various uses, including irrigation, aquarium maintenance, or safely discharged with minimal pollution levels (Alali et al. 2022, 2023; Alnajjar and Ucuncu, 2023). However, while WWTPs are required to meet stringent pollution control standards aligned with sustainable development goals, many plants rely heavily on chemical usage during the treatment process. This approach can lead to excessive consumption of energy and materials, which some argue is at odds with the principles of sustainability (Mizuta and Shimada 2010; Nowak et al. 2015; Panepinto et al. 2016; Wang et al. 2020a, b). Therefore, it is essential to optimize energy usage in these facilities. Energy consumption in WWTPs extends beyond the operations within the plants themselves, such as reactors, aeration systems, and pumps. It also includes the energy required for the production of various chemicals utilized for the treatment processes (Longo et al. 2016). In fact, it is estimated that the energy consumption can account for around 48% of the WWTP's operational costs (Wang et al. 2020a, b). Therefore, analyzing and predicting energy consumption is important for designing WWTPs that are both sustainable and energy efficient. Estimating WWTP's energy consumption enables wastewater professionals to identify the primary forms of energy being consumed and potentially modify consumption patterns accordingly (Torregrossa et al. 2018). The energy consumed in WWTPs is affected by a range of variables, such as wastewater quality, operational factors, weather conditions and aeration processes. These variables make forecasting energy consumption in WWTP a complex task (De Gussem et al. 2014; Panepinto et al. 2016; Molinos-Senante and Maziotis 2022). Estimating energy consumption in WWTPs is a key aspect of achieving better power management, decision-making, environmental protection and sustainable development (Ahmad and Chen 2018). To reach these goals, it is essential to develop appropriate energy consumption models for WWTPs. Various techniques have been presented to model and predict important features of WWTPs, including data-driven and analytical methodologies (Hilal et al. 2022; Safeer et al. 2022; Ly et al. 2022). Analytical methods are dependent on a deep understanding of the fundamental physical processes involved (Cheng et al. 2018). Recent analytical models often use logarithmic, exponential, or linear functions. However, because WWTPs exhibit non-linear behaviors, these simple functions struggle to accurately capture their complexities, especially when dealing with non-numerical variables. Developing an accurate physical model for such complex, high-dimensional, and nonlinear systems is not only challenging but also costly and time-consuming (Haimi et al. 2013). As a result, traditional modeling approaches are often inadequate in effectively describing the relationship between water and energy in WWTPs.

Recent advancements in data science have opened new possibilities to accurately predict critical processes, leading to improved operations, energy savings, and cost reductions. In many instances, the detailed understanding needed for accurate modeling is lacking, which makes data-driven approaches like machine learning (ML), more favorable (Newhart et al. 2019; Kazemi et al. 2021). In the past decade, ML techniques have increasingly attracted attention for their role in optimizing WWTP control. One of the main benefits of adopting ML techniques is their flexibility. Unlike traditional model-based approaches, which can be laborious to design and frequently rely on physical knowledge, ML methods rely only on past data to construct models (Tariq and Deliktaş, 2025; Tariq et al. 2025a). Many ML approaches have been investigated for offering valuable information about the energy consumption of WWTPs (Picos-Benítez et al. 2020; Zhao et al. 2020, Hernández-del Olmo et al. (2019); Alali et al. 2022). Ramli and Abdul Hamid (2019) explored data-driven modeling for WWTP by employing a range of ML techniques. They compared methods including support vector regression, K-nearest neighbors, linear regression and artificial neural networks (ANN) to predict energy consumption. Their findings showed that, out of all the ML techniques examined, ANN produced the highest accurate predictions. Wang et al. (2020a, b) demonstrated the use of ML by analyzing data from the Umea WWTP in Sweden. According to their research, the most important factor affecting the amounts of phosphate and total suspended solids in the treated wastewater is the temperature of the untreated wastewater. Torregrossa et al. (2018) trained ANN and random forests to estimate the cost of energy in WWTPs. They used data from 279 WWTPs in Luxembourg, Denmark, Belgium, France, Netherlands, Austria, and Germany. Their random forest model achieved a high R^2 values of 0.82, slightly outperforming ANN, which reached 0.81. Ahmad and Chen (2018) presented four distinct ML models designed to forecast the energy consumption of pumps within the water source sector. These models were trained using environmental and power usage data as input variables, and the analysis was conducted on both weekly and monthly time scales. Żyłka et al. (2020) assessed the use of a least squares linear regression model for forecasting electricity consumption in a Polish dairy WWTP. Their study

highlighted the significant impact of biological load and air temperature as key variables affecting energy consumption. Similarly, Yang et al. (2020) developed a regression model to predict the energy consumption of WWTPs under various conditions. He identified the COD concentration and influent flow rate as the two important parameters closely correlated with the bioreactor's energy consumption. Additionally, Essa et al. (2020) predicted energy consumption using Egypt's weather-based dataset by employing a hybrid method that combines artificial ecosystem-based optimization and random vector functional link. Yu et al. (2019) estimated the energy consumption of WWTPs utilizing the Bayesian regression method. The study used COD, BOD, total nitrogen and pH as input variables for predicting EC. The correlation analysis revealed that COD (0.96) and BOD (0.86) had the strongest relationships with the target variable. Zhang et al. (2021) utilized the data from China Urban Drainage Yearbook to train a random forest model predicting energy consumption in WWTP. Their trained model achieved strong predictive performance having 0.702 value for R^2. Bagherzadeh et al. (2021) explored the effectiveness of various ML models, including gradient boosting machine, ANN, random forest, and long short-term memory networks, in estimating the energy consumption of WWTP plant in Melbourne. The results indicated that the gradient boosting machine is the most robust model for this example. Boncescu et al. (2021) used Romania's WWTPs data from 2015 to 2017 to train a logistic regression model that can predict energy consumption. Their model demonstrated a good prediction performance with 80% accuracy. However, not all parameters affecting water quality were included in the construction of the logistic regression model. Kumar et al. (2024) applied automated machine learning, Gaussian process regression, boosting and bagging ensemble methods to predict daily streamflow in a semiarid river catchment. Among these, the bagging ensemble model demonstrated the highest predictive accuracy, outperforming even the traditional process-based hydrological model (SWAT). Similarly, Nallakaruppan et al. (2024) employed various machine learning models including support vector machine, decision tree, logistic regression, random forest, and Gaussian Naive Bayes to classify water potability. Among these, the Random Forest model achieved the best performance, with an outstanding accuracy and F1-score of 0.9999, along with a precision of 0.9997 and a recall of 0.998.

Generally, ML are data hungry as they heavily rely on the availability of large amounts of data. However, obtaining data in large quantities is often challenging in many industries, such as finance, healthcare, automotive, and material manufacturing. In these sectors, data is typically protected by strict privacy and security regulations, and there are significant risks associated with data misuse once it is shared with third parties. Moreover, data often exists in isolated silos within these industries. Even integrating data across various divisions within the same firm can encounter significant opposition because of privacy concerns, competitiveness, and complicated administrative processes. Integrating data scattered across various institutions and regions is nearly impossible or expensive. Consequently, these industries often lack sufficient data to train reliable ML models.

Given these constraints regarding data sharing and privacy, there is a significant opportunity to develop new approaches that can address these challenges. Federated machine learning (Fed-ML) offers a promising solution by allowing data from different organizations to be used in training ML models without violating data-related regulations. As a result, Fed-ML has become one of the most advanced technologies in the field of privacy computing. As Fed-ML applications develop further, a significant body of research has surfaced in this area. Currently, research on Fed-ML technology is ongoing, with continuous improvements being made. Fed-ML is being widely applied across various fields, demonstrating its potential while simultaneously addressing emerging challenges. Despite significant advancements in traditional ML techniques, there has been limited exploration of Fed-ML applications in the domain of WWTP performance prediction. Fed-ML offers a decentralized approach to model training, enabling collaboration among geographically dispersed WWTPs while maintaining data privacy and security. By aggregating local model updates from multiple facilities, Fed-ML allows for the development of robust predictive models without the need to centralize sensitive data (Konecný et al. 2016; Banabilah et al. 2022; Ogundokun et al. 2022). Dahane et al. (2024) proposed a federated learning approach combined with knowledge distillation to monitor water quality and assess its suitability for bathing purposes. Their model achieved an accuracy of 90.74% across monitoring stations along the Marne River. Similarly, Rejula et al. (2025) developed a federated learning framework utilizing Long Short-Term Memory (LSTM) networks for decentralized water quality monitoring. By effectively capturing temporal patterns in parameters such as pH, dissolved oxygen, and pollutant concentrations, their model achieved a classification accuracy of 92.3%, while simultaneously enhancing data privacy.

In this study, we propose a Vertical Federated Machine Learning Framework (VFed-ML) to address the challenges posed by traditional centralized ML approaches in the context of WWTPs, particularly concerning privacy concerns and data fragmentation across multiple facilities. By utilizing VFed-ML, WWTPs can collaborate to develop robust predictive models while ensuring that sensitive information remains secure and private. This approach allows for model training on distributed data sources without compromising

data privacy and security. Therefore, this study aims to leverage the advantages of the VFed-ML approach over traditional centralized ML methods to predict energy consumption in WWTPs. To the best of the author's knowledge, this is the first attempt to apply a VFed-ML approach in the context of WWTP performance prediction, offering both practical applicability and methodological advancement. This paper's contribution is summarized as follows:

This study considers a wide range of input variables such as weather, wastewater characteristics, hydraulic data and time for predicting WWTP's energy consumption. Nine ML models including Linear Regressor, XGBoost Regressor, Random Forest Regressor, Decision Tree Regressor, Optimized Random Forest Regressor, and Feedforward Neural Network, Feedforward Neural Network with L2 Regularization, Convolutional Neural Network, and Recurrent Neural Network are compared. The prediction accuracy of these models is assessed using five statistical metrics. The purpose of comparing these ML models is to identify the best-suited model for VFed-ML that allows multiple agencies to collaboratively build a unified model for wastewater treatment processes. VFed-ML algorithm is specifically designed to predict energy consumption in WWTP, while ensuring data security and user privacy.

The structure of this study is as follows: Sect. "Materials and Methods" provides an exploratory data analysis and outlines the various ML models being evaluated. Sect. "Machine Learning Predictions Framework" evaluates the performance of the trained ML. Sect. "Overview of Federated Machine Learning" introduces the fundamental concepts of federated machine learning and its working methodology, followed by an analysis of its results in Sect. "Results and Discussions". Finally, Sect. "Conclusion" concludes the study and offers suggestions for future research and potential improvements.

Table 1 Measured variables in Melbourne's WWTP

Parameters (abbreviation)	Unit
Average inflow (Q_{in})	m^3/s
Average outflow (Q_{out})	m^3/s
Energy consumption (Ec)	MWh
Ammonia (NH_4.N)	mg/L
Biological oxygen demand (BOD)	mg/L
Chemical oxygen demand (COD)	mg/L
Total nitrogen (Tnit)	mg/L
Average temperature (T_{avg})	°C
Maximum temperature (T_{max})	°C
Minimum temperature (T_{min})	°C
Atmospheric pressure (AP)	hPa
Average humidity (H)	%
Total rainfall and snowmelt (Pr)	mm
Average visibility (VIS)	Km
Average wind speed (WS_{avg})	Km/h
Maximum wind speed (WS_{max})	Km/h
Year	-
Month	-
Day	-

Materials and Methods

Description of Data

This work utilizes data from the WWTP in Melbourne which was accessed on Apr 5, 2024, via Kaggle (https://www.kaggle.com/code/d4rklucif3r/waste-water-treatment-plant-luciferml-viza). The dataset includes daily measurements of chemical oxygen demand (COD), biological oxygen demand (BOD), Ammonia (NH_4.N), total grid power consumption, total nitrogen (Tnit), minimum temperature (Tmin), maximum temperature (Tmax), average temperature (Tavg), maximum wind speed (WSmax), average wind speed (WSavg), total rainfall and/or snowmelt (Pr), average relative humidity (Havg), atmospheric pressure (AP), average visibility (VIS) (Bagherzadeh et al. 2021; Alali et al. 2022, 2023). The dataset contains 1382 records collected between Jan 2014 and June 2019 and includes the 19 variables detailed in Table 1.

Before developing predictive models, it is crucial to analyze the data using various visualization plots. For example, time-series data can be plotted to visually identify the variation and trends in the data. Additionally, data visualization can reveal outliers or missing values that may require attention during data preprocessing. Figures 1, 2, 3 and 4 illustrates the daily evolution of multivariate time-series data variables collected from Melbourne's WWTP.

The distribution, outliers and the overall characteristics of energy consumption data are illustrated in Figs. 5 and 6. Figure 6 presents boxplots and scatterplots of energy consumption in relation to yearly power consumption at the WWTP during the period from 2014 to 2019. It's important to note that the data for 2019 covers only the first 6 months, resulting in a more compact boxplot for that year compared to the others. Figure 6 shows that in 2018, the energy consumption distribution experienced a slight decline in standard deviation in contrast to 2017. This reduction might be attributed to the WWTP operator's efforts in improved management. Understanding these patterns can aid in enhancing energy consumption predictions, enabling more effective resource allocation and planning.

The Pearson correlation coefficient was employed to calculate the degree of linear correlation between each variable and daily energy consumption, as presented in Fig. 7. This analysis was crucial for selecting the most relevant features for the VFed-ML model while minimizing redundancy and mitigating the risk of overfitting. The results indicated that

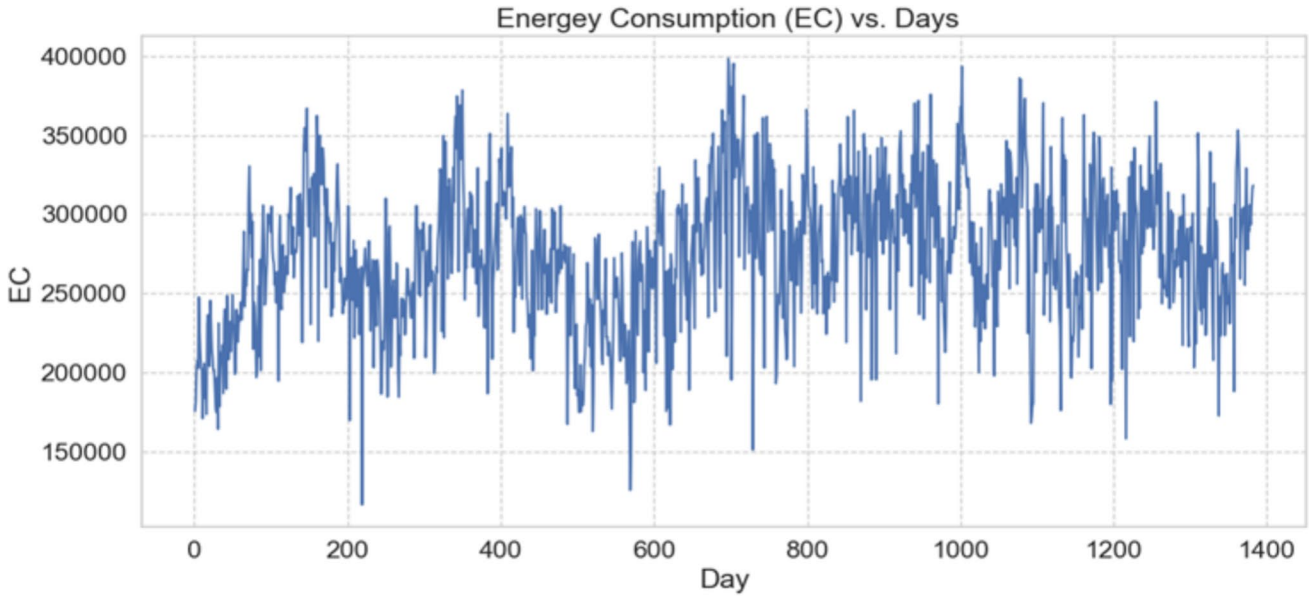

Fig. 1 Daily distribution of energy consumption

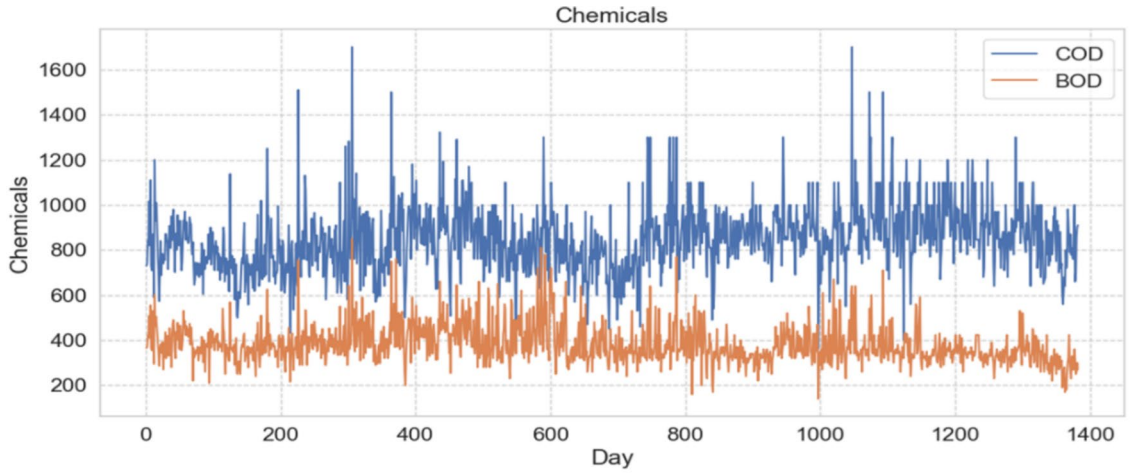

Fig. 2 Daily distribution of COD and BOD

energy consumption (EC) at the wastewater treatment plant is influenced by both weather and seasonal variations. For instance, a correlation coefficient of −0.25 was observed between daily Max. Temp and EC, highlighting the role of climatic factors. Among the time-related variables (day, month, and year), the 'month' variable exhibited the strongest correlation with daily energy consumption, whereas 'day' and 'year' showed lower correlation. Consequently, only 'month' was retained, and the others were excluded to enhance model efficiency without sacrificing predictive capability. In the group of wastewater quality parameters, strong positive correlations were found between COD and Tnit (0.68), and between COD and BOD (0.52). Regarding climate-related variables, parameters such as Avg. Temp, Max. Temp, Min. Temp, and Avg. Hum emerged as impactful predictors. However, some of these variables exhibited very high correlations such as Avg. Temp with Max. Temp (0.92), Min. Temp with Max. Temp (0.76), and Avg. Hum with Avg. Temp (−0.55), which can degrade machine learning model performance if not addressed. Thus, redundant variables were carefully removed to maintain the independence of features, improving both model generalization and computational efficiency. This thorough variable selection process ensures that the final set of input features not only maintains the essential predictive information but also avoids unnecessary complexity, supporting the goal of developing a robust, accurate, and efficient federated learning framework for wastewater treatment plant energy consumption prediction.

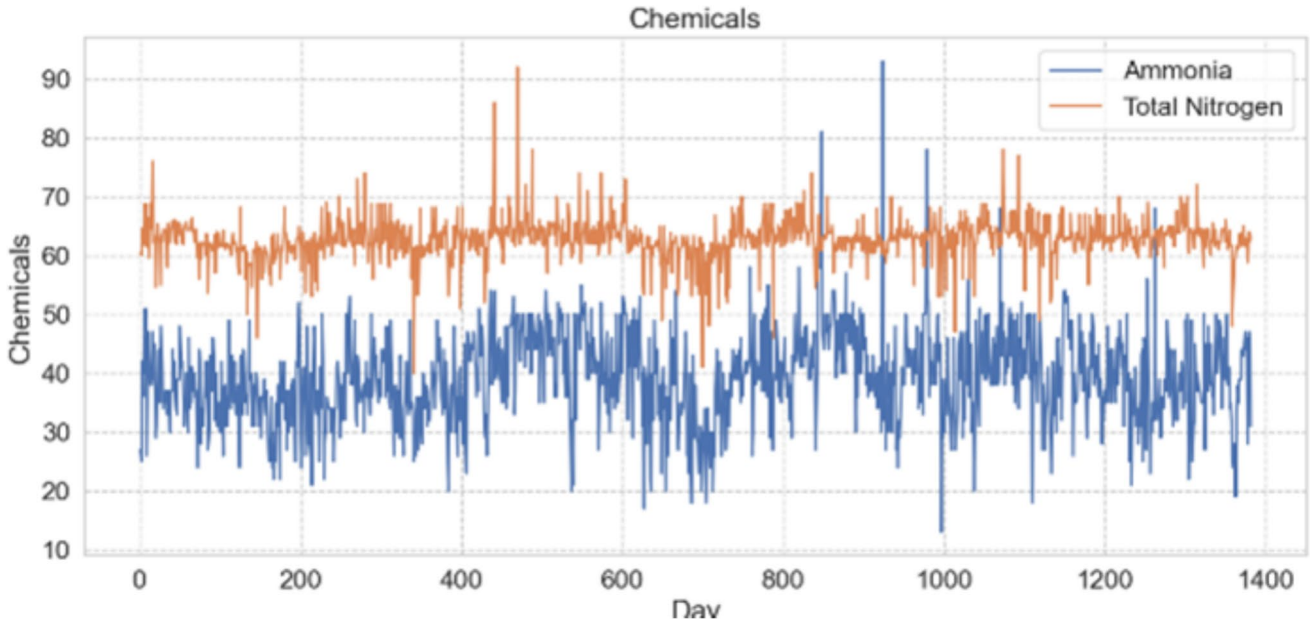

Fig. 3 Daily distribution of Ammonia and Total Nitrogen

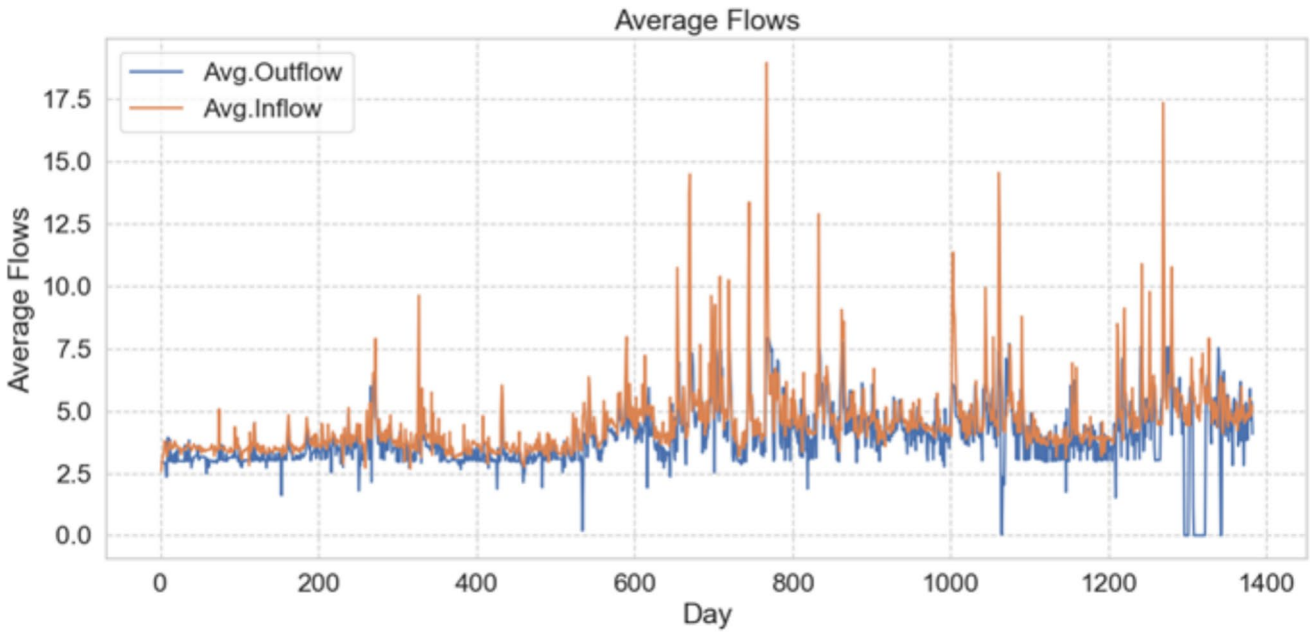

Fig. 4 Daily distribution of Avg. Inflow and Avg. Outflow

Model Descriptions

This paper examines the effectiveness of commonly used ML techniques for predicting energy consumption in WWTPs. These predictions are influenced by various reasons such as weather conditions (temperature and precipitation), volume and composition of incoming wastewater, the specific treatment processes utilized and seasonal variations. The primary goal of this study is to evaluate the effectiveness of different ML algorithms, including Linear Regressor (LRG), Optimized Random Forest Regressor with GridSearchCV (ORFR-GS), three types of Ensemble Learning models (XGBoost Regressor, Random Forest Regressor (RF), Decision Tree Regressor with GridSearchCV (DTR-GS)) and four different Artificial Neural Network models (Feedforward Neural Network (FFN), Feedforward Neural Network with L2 Regularization (FFN-L2R), Convolutional Neural Network (CNN), and Recurrent Neural Network with LSTM Cells (RNN-LSTM)).

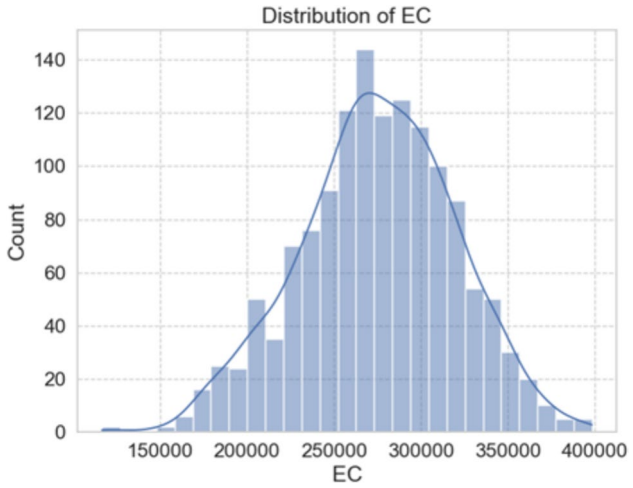

Fig. 5 History distribution of the collected data of energy consumption

Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are robust computational tools modeled after biological neural systems to tackle intricate real-world challenges such as function approximation, pattern recognition, clustering, predictive modeling, and image restoration. By replicating the structure of human neural networks, ANNs adeptly extract meaningful information from data through their capacity to learn and generalize (Tariq et al. 2025b). These advanced algorithms excel at capturing non-linear relationships between inputs and outputs, rendering them highly effective for modeling complex processes, including those in wastewater treatment facilities (WWTPs). An ANN functions by aggregating the weighted products of inputs, which are then processed through an activation

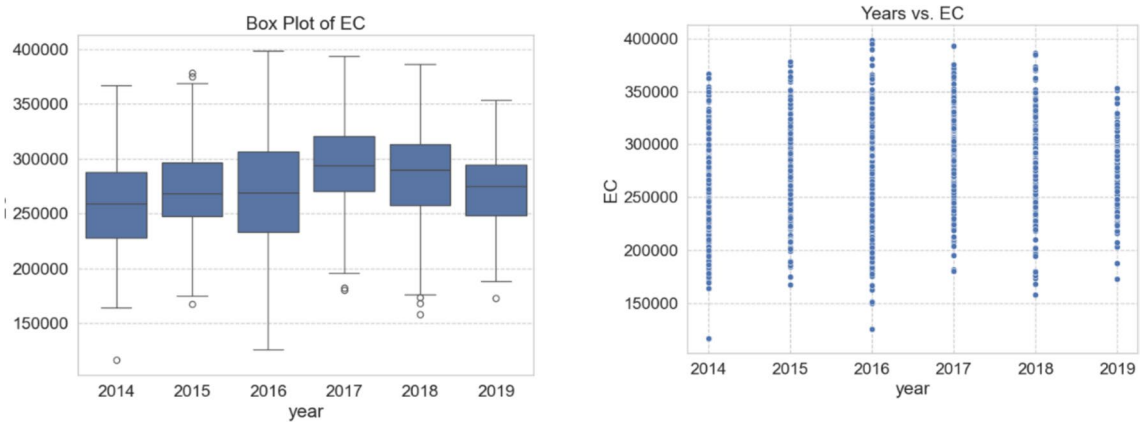

Fig. 6 Box plot and scatter plot of energy consumption over the years

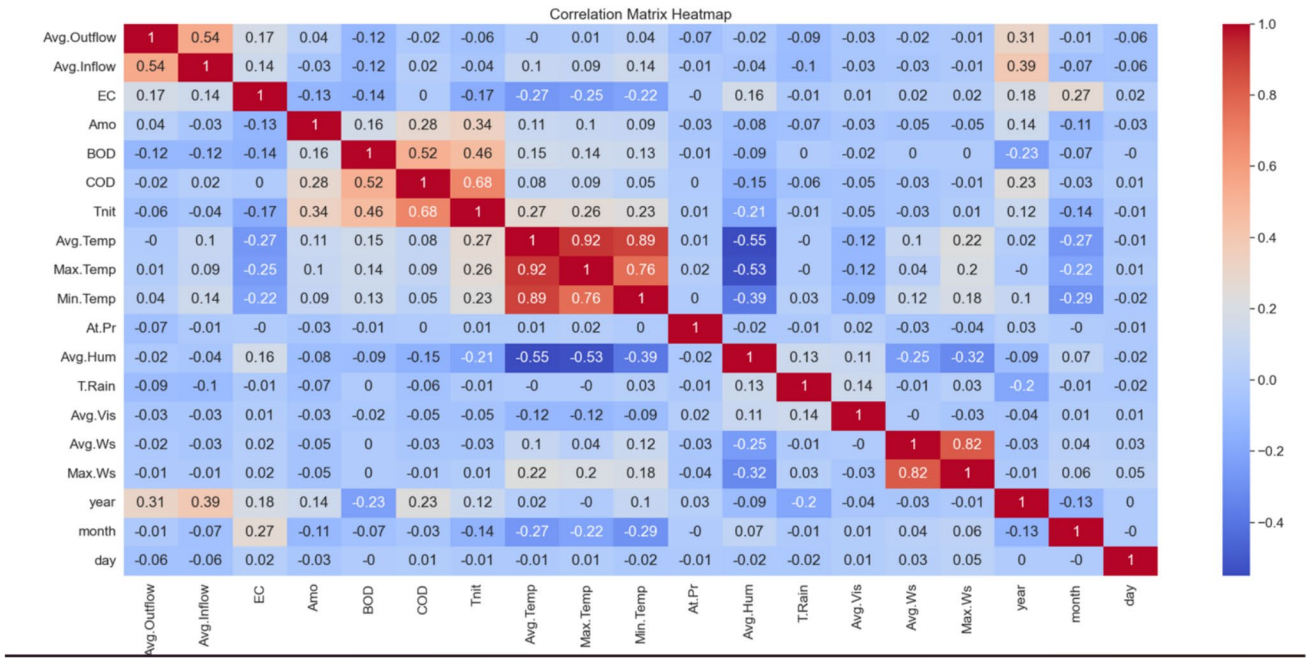

Fig. 7 Correlation map between measured variables

function such as ReLU, Sigmoid, and Tanh to produce the output for a given layer. This activation function introduces non-linearity into the model that empowers ANNs to master advanced tasks. The core relationship between inputs and outputs is mathematically written as:

$$y_k = f_0 \left[\sum_j w_{kj} . f_h \left(\sum_i w_{ji} x_i + b_j \right) + b_k \right] \quad (1)$$

Here, x represents the input vector, w_{ji} denotes the connection weight linking the ith neuron in the input layer to the jth neuron in the hidden layer, and w_{kj} signifies the weight from the jth neuron in the hidden layer to the kth neuron in the output layer. The terms b_j and b_k indicate the biases associated with the hidden and output layers, respectively, while f_h and f_o correspond to the activation functions applied to the hidden and output layers.

The performance of ANNs hinges on their structure, initialization, and training parameters. The multi-layer perceptron, a type of Feedforward Neural Network (FNN), proves highly potent in engineering applications when refined using the back-propagation algorithm. FNNs provide straightforwardness and versatility, rendering them well-suited for basic predictive tasks. Nevertheless, discerning complex patterns demands careful architectural design and regularization techniques. Studies frequently employ ANN models with reduced hidden layers to simplify complexity and speed up the training process. Diverse configurations, such as three- and four-layer architectures with varying neuron numbers in hidden layers are evaluated to identify the most optimal models. Below is a brief description of the ANN models considered in this study:

1. *Feedforward Neural Networks (FNNs)*: This is the simplest form of ANN where information moves in one direction, from input nodes, through hidden layers, to output nodes, without looping back. FFNs are a fundamental building block in deep learning. Their simplicity and versatility make them suitable for a variety of tasks. FFNs are effective for basic prediction tasks but may struggle with more complex patterns. However, careful consideration of architecture, training process, and regularization techniques is essential to achieve optimal performance.
2. *Feedforward Neural Networks with L2 Regularization (FFN-L2R)*: An extension of FFNs that includes L2 regularization to prevent overfitting by penalizing large weights. This enhances the model's capacity for generalization. Dropout prevents the network from overfitting to the training data and helps it learn more robust features by randomly removing neurons during training. Dropout ensures that the model does not depend on a particular set of neurons, making it more resilient and improving its performance on unseen data.
3. *Convolutional Neural Networks (CNNs)*: CNNs are a class of deep neural networks primarily used for analyzing visual data. Their ability to learn hierarchical feature representations makes them well-suited for tasks requiring high-level abstraction. Although typically used for image processing, CNNs can be adapted for time-series data to capture spatial hierarchies and patterns, making them suitable for recognizing localized features in data.
4. *Recurrent Neural Network with LSTM (RNN-LSTM)*: RNNs with LSTM units are a class of neural networks specifically created for processing sequential data. RNNs are different from standard feedforward neural networks as they feature directed cycle connections, which allow them to remember previous inputs. Their ability to capture long-term dependencies makes them ideal for tasks such as time-series prediction, natural language processing, and speech recognition.

Decision Tree Regression

Decision Tree Regression (DTR) is a predictive modeling technique that divides a dataset into smaller subsets and predicts numerical outcomes using a tree-like structure. DTR divides the data recursively according to feature values, averages each subset's values to produce predictions, and uses mean squared error to reduce the target variable's variance. Deep trees can result in overfitting and poor generalization, but DTR's intuitive structure makes it easy to understand and quick to train. Pruning and hyperparameter optimization techniques, such as GridSearchCV, are employed to solve this issue by streamlining the model, avoiding overfitting, and improving performance on unseen data. Additionally, DTR serves as the foundation for sophisticated ensemble methods such as Random Forest, which builds several trees to decrease overfitting and enhance accuracy and robustness. Despite its strengths, DTR's effectiveness is dependent on data quality, may struggle with predictions outside the training dataset, and can be sensitive to small changes in the data, resulting in different tree structures.

1. *Decision Tree Regressor with GridSearchCV*: GridSearchCV is a tool provided by Scikit-learn that performs hyperparameter tuning. It searches for the best hyperparameters for a decision tree model over specified parameter values and evaluates each combination using cross-validation. The best combination is then selected based on the performance metric specified. The process of finding the best hyperparameters for a given model is completely automated.

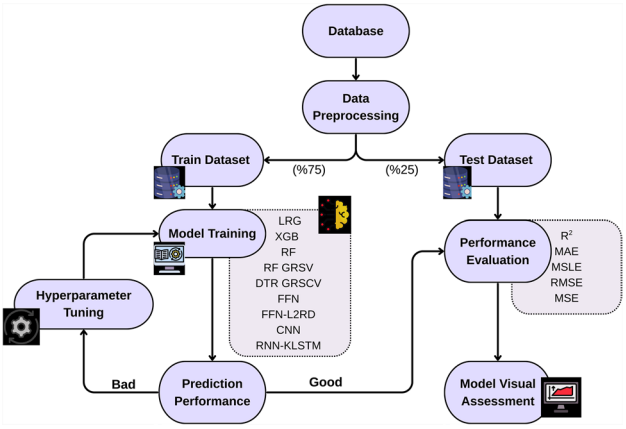

Fig. 8 General framework of the ML modeling process

2. *Optimized Random Forest Regressor with GridSearchCV*: This model is an enhanced version of the Random Forest algorithm, that builds multiple decision trees during training and averages their predictions for regression tasks. This approach helps reduce overfitting and improves the model's generalization ability. ORFR-GS further enhances performance by efficiently tuning hyperparameters through GridSearchCV, which systematically searches over a predefined parameter grid and applies cross-validation to find the optimal model configuration. This combination ensures a more accurate and robust model for regression tasks.

Ensemble Learning Models

Ensemble learning is a machine learning approach that enhances predictive accuracy by combining multiple models to address challenges like class imbalance, concept drift, and high dimensionality. It is particularly effective for regression tasks, where models like decision trees or neural networks are aggregated to produce robust predictions. However, ensemble models can be computationally intensive and less interpretable, posing challenges for applications requiring transparency. Ensemble pruning selects a subset of models to reduce complexity while maintaining performance, and diversity techniques promote complementary model behaviors to simplify ensembles. Popular ensemble learning methods include Bagging, which trains models on random data subsets and averages their predictions; and Boosting, which sequentially corrects errors (Tariq et al. 2024a). Below is a brief description of the ensemble learning models considered in this study:

1. XGBoost Regressor: The XGBoost is a highly efficient gradient boosting implementation, known for its ability to handle large datasets and missing data. It often outperforms other algorithms due to its regularization techniques and parallelization across multiple cores (Chen and Guestrin 2016). XGBoost is suitable for both

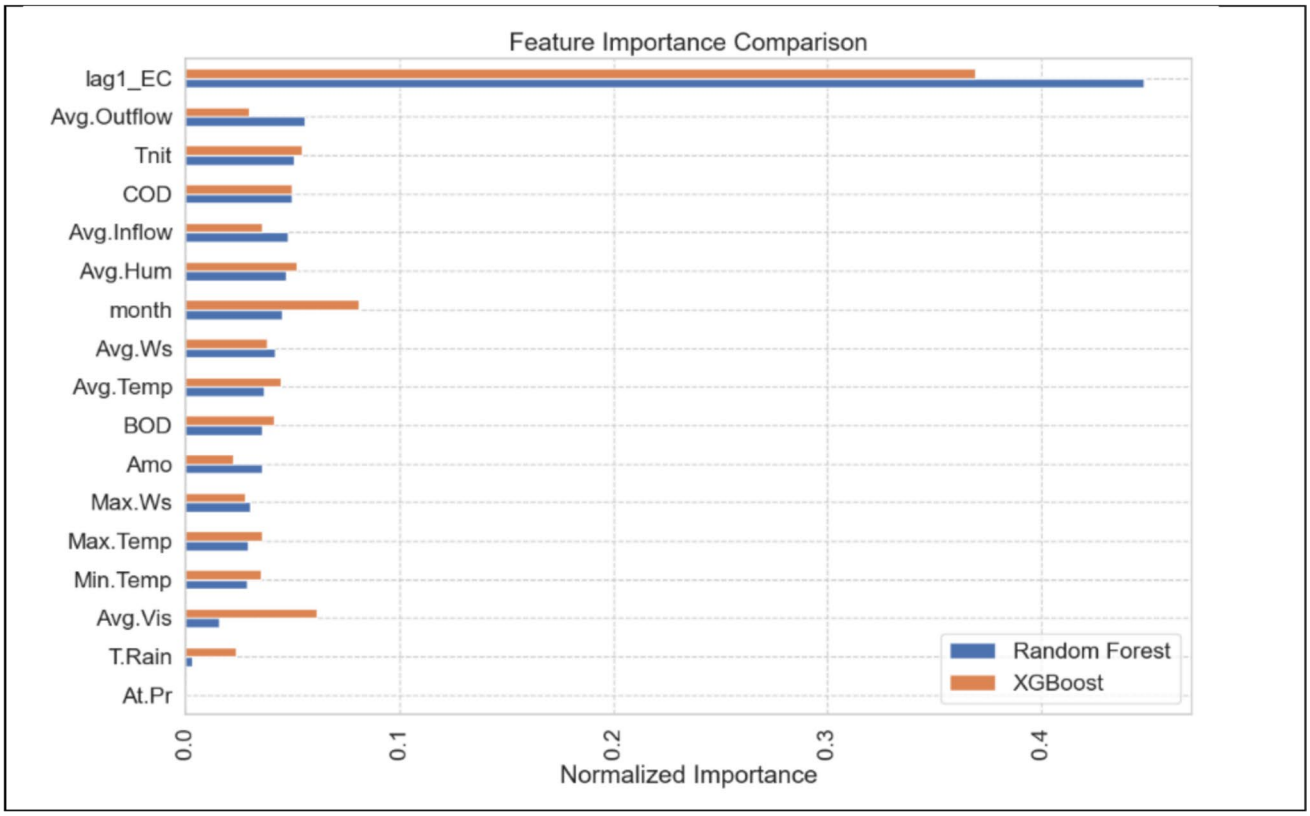

Fig. 9 Identification of important features in the dataset using XGBoost and RF methods

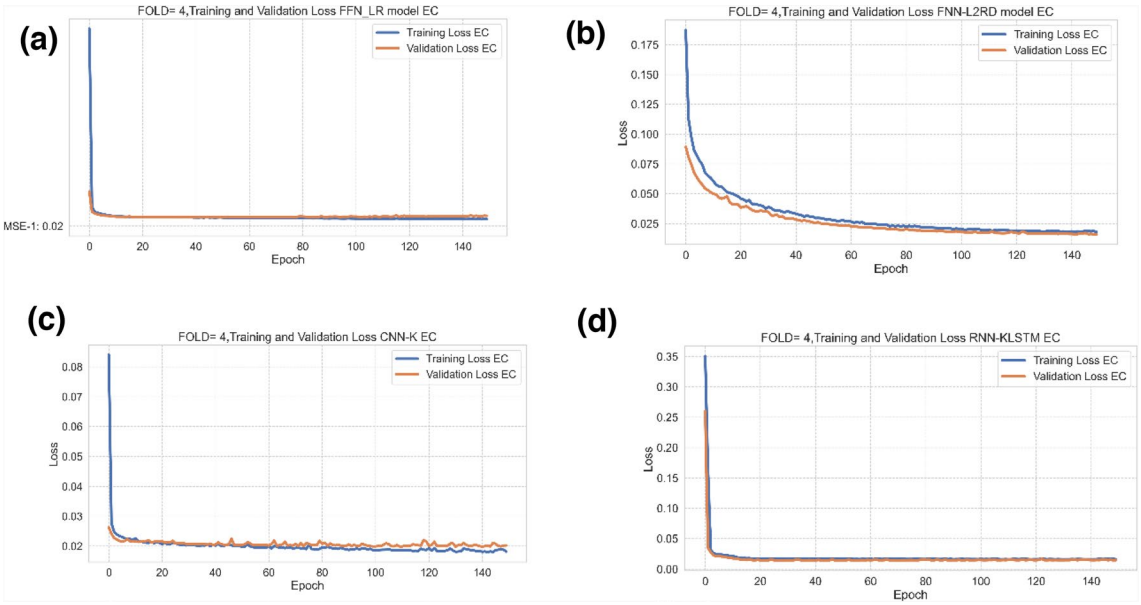

Fig. 10 **a** Feedforward Neural Network (FFN). **b** Feedforward Neural Network with L2 Regularization and Dropout (FFN_L2RD). **c** Convolutional Neural Network Model (CNN). **d** Recurrent Neural Network with LSTM (RNN-LSTM)

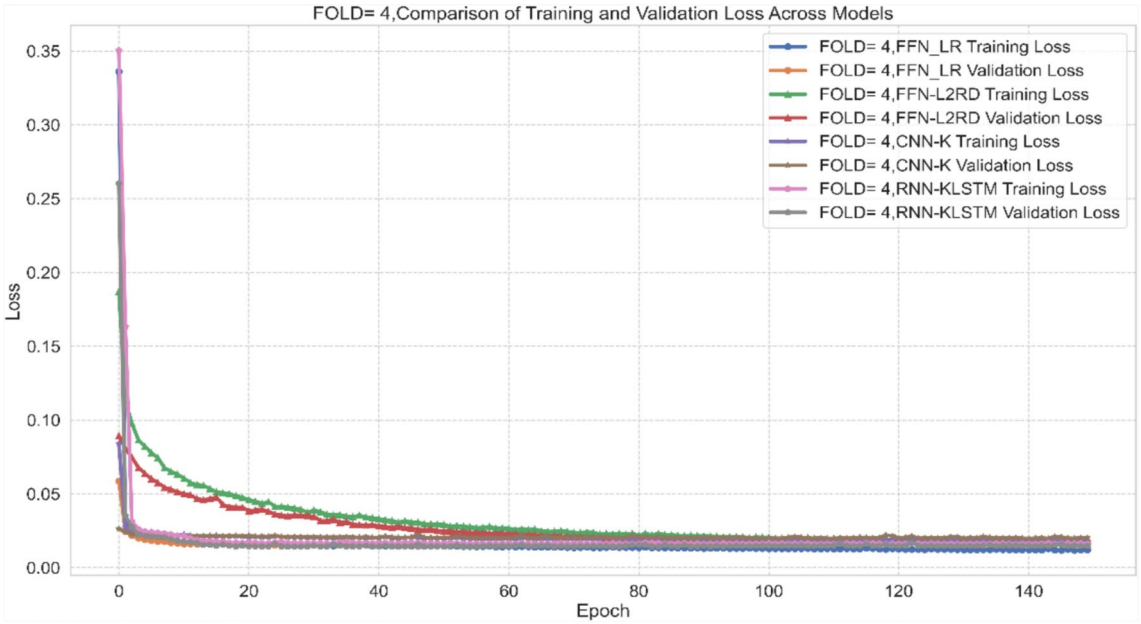

Fig. 11 Comparison of training and validation loss of each ML model

regression and classification tasks, making it a versatile choice for various machine learning challenges (Tariq et al. 2024b). Using GridSearchCV with XGBoost allows for efficient hyperparameter tuning through cross-validation, ensuring optimal performance and generalization. Recently, Polat et al. (2025) proposed a PSO-XGBoost hybrid model to automatically identify the hyperparameters and enhance the prediction accuracy of a model without any manual interference. This model significantly reduced computational complexity and time compared to traditional analysis. The objective function can be formulated as follows:

$$y_i(t) = y_i(t-1) + f_t(x_\imath)$$

$$\xi_1, \xi_2, \xi_3, , , , , , \xi_m = argmin \sum_{i=1}^{N} L(y_i, y_i(t)) + \sum_{j=1}^{t} \Omega(f_j)$$

Table 2 Comparison of the performance of the models using various metrics

Model	MSE	RMSE	MSLE	MAE	R^2
LRG	0.016928	0.130109	0.099158	0.0075492	0.434271
XGB	0.018468	0.135898	0.104133	0.0080937	0.382810
RF	0.016831	0.129737	0.098792	0.0074483	0.437497
RF GRSV	0.020122	0.141852	0.11028	0.0088317	0.32753
DTR GRSCV	0.016740	0.129385	0.098461	0.0074233	0.440550
FFN	0.021753	0.147491	0.111957	0.0097056	0.273018
FFN-L2RD	0.018500	0.136017	0.106159	0.0081658	0.381721
CNN	0.025395	0.159359	0.125	0.0113137	0.15130
RNN-KLSTM	0.016973	0.13028	0.100383	0.0074418	0.432776

here, $f_t\,(x_i)$ represents the base learner, $y_i\,(t)$ is the regression tree aimed for optimization, Ω indicates the complexity of the regression tree, and $\xi_1, \xi_2, \xi_3, , , , , , \xi_m$ is the leaf nodes of the target model.

2. Random Forest Regressor: The Random Forest Regressor (RF) is an ensemble learning method that builds multiple decision trees and averages their predictions to improve performance and reduce overfitting. It works well with both numerical and categorical data and handles missing values effectively. Using GridSearchCV with Random Forest allows for efficient hyperparameter tuning through cross-validation, ensuring the model generalizes well by balancing bias and variance. Additionally, Random Forest provides feature importance estimates, offering insights into the contribution of each feature. Its versatility and robustness make it a powerful tool for regression tasks across various domains.

Machine Learning Predictions Framework

This section investigates the performance of various ML models described earlier for predicting energy consumption in WWTPs. The best performing model is identified by comparing the results of each model using a range of statistical metrics. This study employs Python as a primary tool to train and implement different ML algorithms. Python provides a platform for developing, optimizing, and evaluating these models to perform accurate and efficient predictions for wastewater management purposes. Various open-source libraries in Python 3.8 such as Pandas for data engineering, Scikit-Learn and Keras for ML models, Matplotlib and Seaborn for visualization were implemented. The general ML framework adopted to train these models is illustrated in Fig. 8.

In the training database, lagged data (lag1_EC) is introduced as an additional input variable to better capture the dynamic nature of energy consumption. This approach investigates the impact of incorporating past information on the prediction accuracy of the ML models under consideration. Consequently, the ML models are trained using a reduced dataset in which only the relevant input variables are included, and redundant variables are removed. XGBoost and Random Forest (RF) models are used to identify important input variables within the dataset using feature importance method. Figure 9 illustrates the significance of each input variable in predicting energy consumption for the WWTP. A higher amplitude signifies a greater impact of that variable on the energy consumption prediction. Both XGBoost and Random Forest indicate that lag1_EC has a significant impact in predicting energy consumption, with a high importance score of approximately 0.53. This suggests that recent energy consumption has a strong influence on current energy usage in WWTP.

After incorporating Lag1_EC data as an input variable, the dataset was splitted with 75% of the data allocated for training the ML models. The trained models were then evaluated using the remaining 25% of the data as the test set. Model performances were further evaluated by using the k-fold cross-validation technique. It involves repeatedly splitting the data into different train and test subsets, allowing the model to be trained and tested multiple times on various parts of the data. A more reliable estimate of the model's performance is provided by this cross-validation technique.

Model Results and Discussions

The performance of the different neural network models during the training process and their performance on validation dataset are evaluated using loss curves. These curves help ensure that the models perform effectively not only on the training data but also maintain their accuracy when exposed to new, unseen data. Ideally, the loss curves should decrease over time as the model learns from the data. The loss curves of the neural network models during training and validation are presented in Figs. 10 and 11. The results show that both the training and validation loss curves closely overlap each other, indicating that the models are not overfitting. This implies that ANN models are learning effectively and are capable of generalizing unseen data.

The prediction accuracies of all ML models are assessed using various metric functions, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Squared Logarithmic Error (MSLE), and Coefficient of Determination (R^2). These metric values can be used for comparing the performance of each model in predicting energy consumption. The value of these metrics for all the ML models on the testing data is

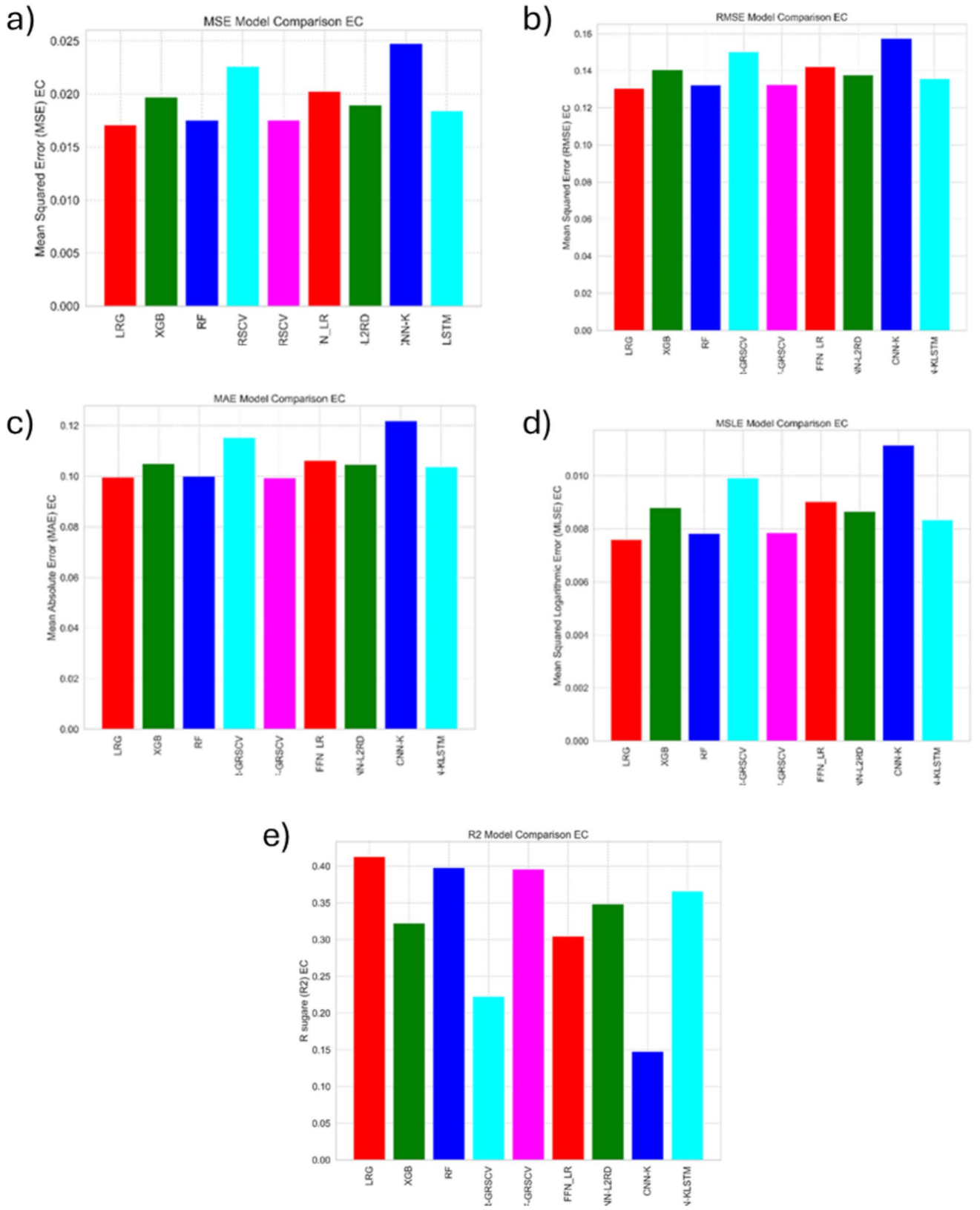

Fig. 12 Comparison of model performance with bar plots for **a** MSE, **b** RMSE, **c** MAE, **d** MSLE and **e** R^2 metrics

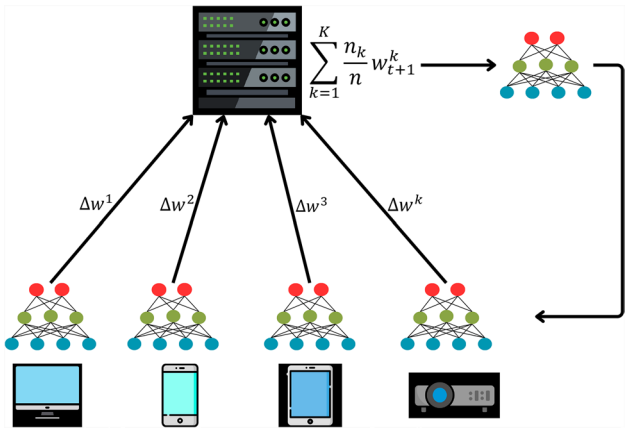

Fig. 13 The basic framework of Fed-ML

provided in Table 2. This table reveals that the LRG and RNN-KLSTM models outperformed all others, achieving the lowest values in the performance metrics, achieving an MSE, RMSE, MSLE, MAE and R^2 value of 0.0169, 0.1301, 0.0991, 0.00754, and 0.4342 respectively. Among the other models, RF, DTR-GRSCV and XGB also demonstrated strong performance, with MSE, RMSE, MSLE, MAE, and R^2 errors approximately at 0.0175, 0.1323, 0.0998, 0.0078, and 0.39, respectively. When comparing the performance of the ANN models, the RNN-KLSTM yielded the best results, with an MSE of 0.0169, RMSE of 0.13028, MSLE of 0.10083, MAE of 0.008744, and R^2 error of 0.43277. Similarly, the performance of FFN-L2RD was quite close to that of RNN-KLSTM, with the metrics registering at MSE 0.0185, RMSE 0.1360, MSLE 0.1061, MAE 0.00816, and R^2 error 0.3817. On the other hand, the CNN model exhibited the poorest performance, with the highest MSE of 0.0253, RMSE of 0.1593, MSLE of 0.125, MAE of 0.01131, and the lowest R^2 error of 0.15130. These metrics are plotted in Figs. 12 to visually compare the performance of all ML models used in this study.

In summary, ML models have proven to be an effective technique for predicting energy consumption in WWTPs. This predictive capability can assist WWTPs in reducing energy expenses by optimizing various aspects of the treatment process. Nevertheless, there is still room for improvement in the accuracy of machine learning-based energy consumption predictions in WWTPs. Even though variable selection methods were used to optimize the prediction model, it is crucial to recognize that the predictive accuracy of model might still be affected by variables that were excluded.

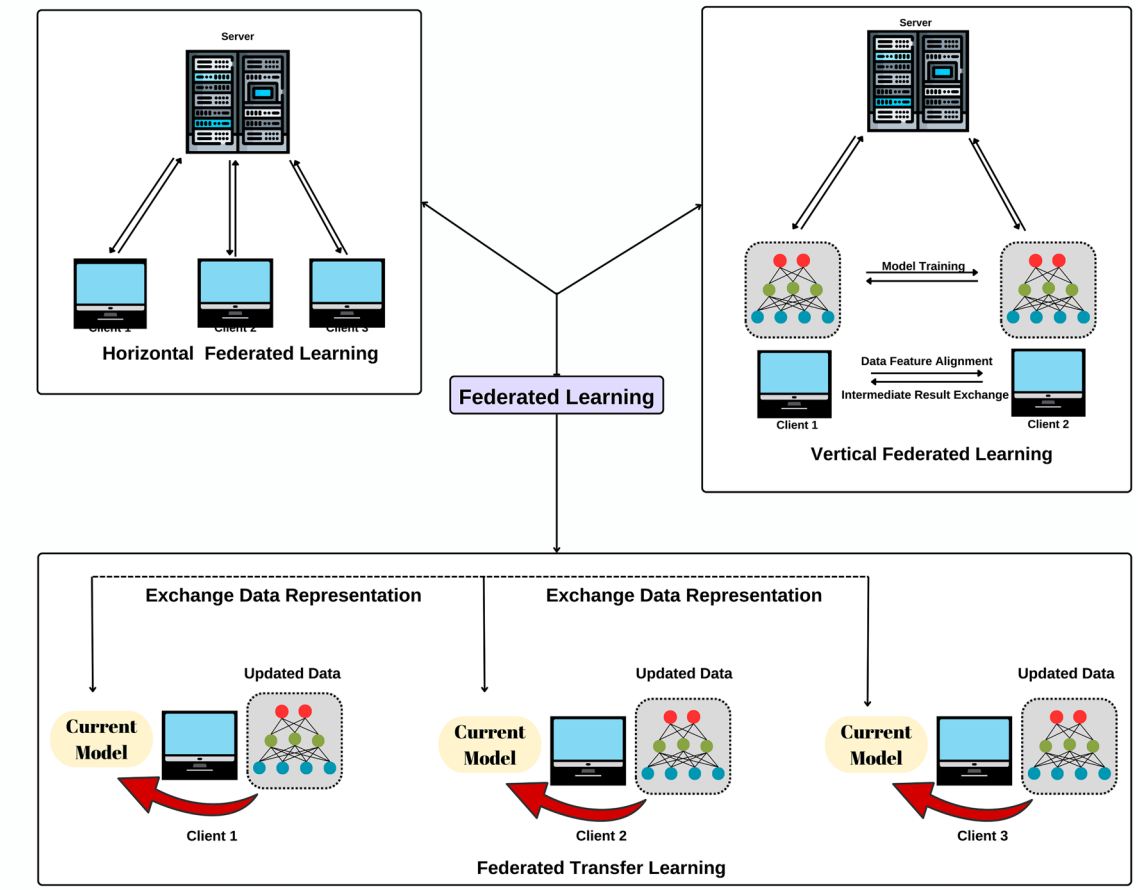

Fig. 14 Description of HFed-ML and VFed-ML

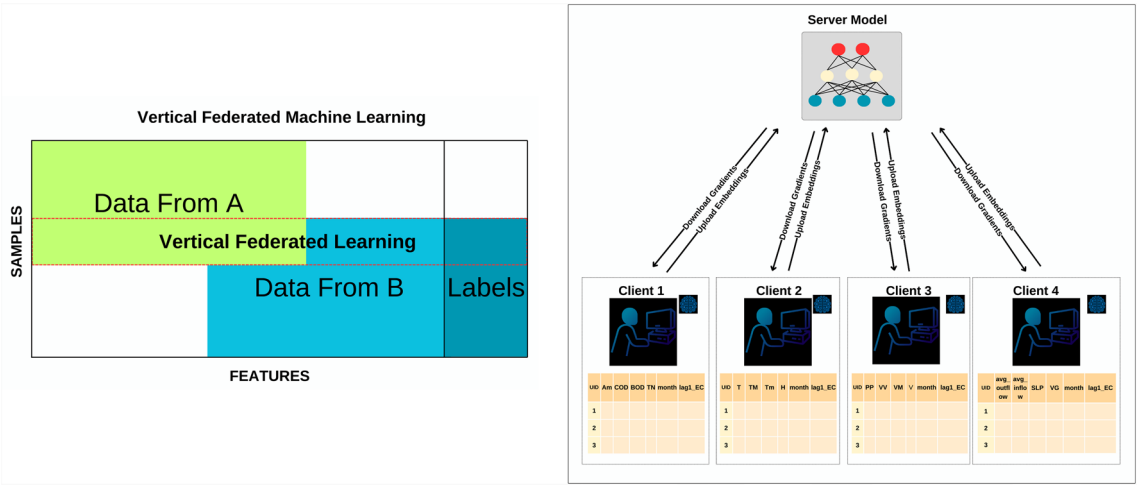

Fig. 15 Vertical Federated Learning

Overview of Federated Machine Learning

Federated machine learning (Fed-ML) was originally presented by Google in 2016, allowing individuals to collaboratively train a centralized ML model while securing the local storage data on their mobile device. (Konecný et al. 2016; Zhu and Jin., 2019; Lim et al. 2020). By doing so, the Fed-ML technique helps to prevent the leakage of private information, ensuring data privacy and security throughout the training process. Fed-ML enables several clients to execute ML algorithms together without requiring personal data to leave the local environment (Liu et al. 2020; Aono et al. 2017; Saha and Sheikh 2021). In Fed-ML, data training occurs locally on each client, the exchange of parameters is established between server and client. This exchange is called communication, and it doesn't require data sharing. The role of server is limited to aggregating these parameters to update the global model. This approach not only protects local user data but also conserves the server's storage and computing resources. Fed-ML can achieve a high-performing global model through this client–server communication, which contrasts with traditional centralized training methods where all local datasets are collected and processed on a central server (Saha et al. 2020).

In a Fed-ML methodology, it is typically considered that all clients collectively support the creation of common data policies. As the data transfer between clients does not take place directly, this approach maintains data integrity and safeguards user privacy. The overall process of Fed-ML as depicted in Fig. 13 can be outlined as follows: First each client downloads a model from the central server. Second, each client uses their personal data to locally train their model until it reaches convergence. Thirdly, the model parameters are encrypted by the client before being uploaded to the server. Lastly, the server employs the Fed-ML algorithm to aggregate the uploaded parameters, and then the global model is updated for the subsequent training cycle. This process repeats in a loop, with continuous communication between the server and client, until convergence is reached in the global model (Wen et al. 2023).

Consider N clients participating in the Fed-ML, each aiming to combine their data their data $\{P_1, P_1, \cdots, P_N\}$ to obtain a unified model. Common practice is to aggregate all the data from all clients and use the entire dataset $P = P_1 \cup P_2 \cup \cdots \cup P_N$ for training a ML model. On the

Fig. 16 Feedforward neural network with dropout and L2 regularization

```
def create_fnnl2r_model():
    model = Sequential([
        Dense(64,input_shape=(X_train.shape[1], 1),activation='relu', kernel_regularizer=l2
        Dropout(0.2),
        Dense(32, activation='relu', kernel_regularizer=l2(0.001)),
        Dropout(0.2)
        Dense(1)
    ])
    model.compile(optimizer=Adam(learning_rate=0.001),
                  loss='mean_squared_error',
```

```python
from typing import List, Tuple

import flwr as fl
from flwr.common import Metrics, Parameters, Scalar
import numpy as np

# Define metric aggregation function
def weighted_average(metrics: List[Tuple[int, Metrics]]) -> Metrics:
    # Multiply mae of each client by number of examples used
    maes = [num_examples * m['mae'] for num_examples, m in metrics]
    examples = [num_examples for num_examples, _ in metrics]

    # Aggregate and return custom metric (weighted average)
    return {'mae': sum(maes) / sum(examples)}

# Dummy evaluation function (replace with actual evaluation logic)
def evaluate_model(parameters: Parameters) -> Tuple[float, float]:
    # Dummy logic for evaluation
    # Replace this with actual model evaluation using validation data
    loss = np.random.random()  # Random loss value
    mae = np.random.random() * 1000  # Random MAE value
    return loss, mae

# Define a custom evaluation function
def evaluate(server_round: int, parameters: Parameters, config: dict) -> Tuple[float, Metrics]:
    loss, mae = evaluate_model(parameters)
    return loss, {'mae': mae}

# Define strategy
strategy = fl.server.strategy.FedAvg(
    evaluate_fn=evaluate,  # Custom evaluation function
    evaluate_metrics_aggregation_fn=weighted_average  # Aggregation function for metrics
    )

# Start Flower server
fl.server.start_server(
    server_address="0.0.0.0:8080",
    config=fl.server.ServerConfig(num_rounds=10),
    strategy=strategy,
)
```

Fig. 17 A central server script within Flower framework

other hand, in Fed-ML framework clients cooperatively train a shared model by ensuring that no user shares their personal information with third parties. In Fed-ML, each client's loss function is computed using a weighted aggregation method and learning is accomplished by reducing this function. Fed-ML's objective is to reduce the objective function defined as:

$$\min f(w) = \sum_{k=1}^{N} \frac{n_k}{n} f(w) \tag{2}$$

where *f(w)* denotes the kth client's objective function, n_k represents the kth client's total of data and *N* is the number of clients. The goal is to find the model parameters w that minimize this weighted sum of the loss functions across all participating clients.

Fed-ML approaches can be broadly classified into three types: Horizontal Federated Learning (HFed-ML), Vertical Federated Learning (VFed-ML), and Federated Transfer Learning (FTL), depending on how much the data characteristics in the client datasets overlap. Each of these categories is designed to address different practical challenges in data distribution and feature alignment. The specific categorization is illustrated in Fig. 14.

For an extensive explanation regarding the classification of Fed-ML according to the data distribution properties, refer to Wen et al. (2023), Saha and Ahmad (2021), and Yang et al. (2019). In this paper, we briefly introduce Vertical Federated Learning (VFed-ML), which is utilized to establish our federated agencies. VFed-ML is particularly suited for building a unified model that ensures safety, efficiency, and compliance with multi-source data applications, such as those involved in wastewater treatment processes.

Vertical Federated Learning

Vertical Federated Learning (VFed-ML) is a decentralized machine learning approach, suitable for problems where datasets have the same sample ID space but differ in their feature spaces as illustrated in Fig. 15. This means that the participants in VFed-ML have data concerning the same

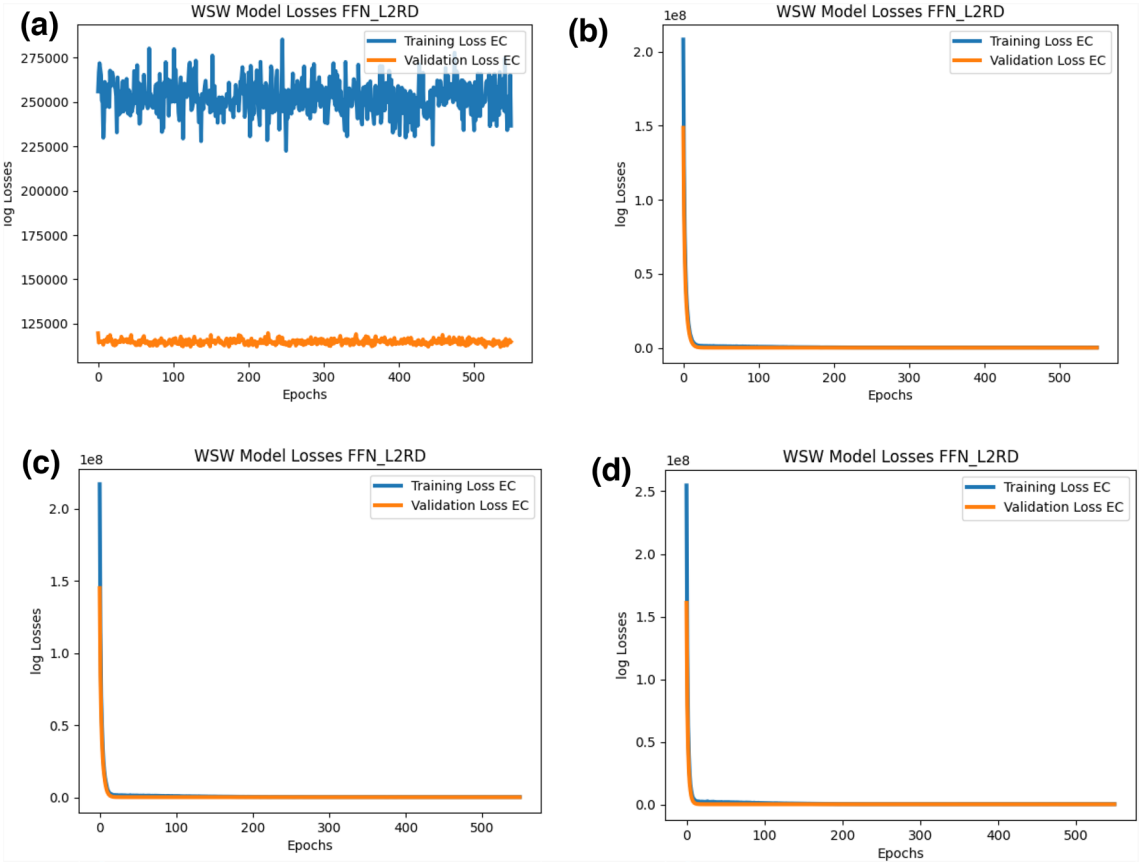

Fig. 18 **a** Client 1: Wastewater related variables at round 1. **b** Client 1: Wastewater related variables at round 2. **c** Client 1: Wastewater related variables at round 5. **d** Client 1: Wastewater related variables at round 10

entities but possess different types of information about them, allowing them to collaboratively build a model while maintaining data privacy.

In VFed-ML, data is partitioned vertically, meaning that each client possesses different attributes (features) related to the same set of users. For example, one client might have demographic data while another has transactional data, but both datasets pertain to the same individuals. These clients can collaborate to train a model with the assistance of a central server. Each client calculates the training gradient locally and applies encryption or other privacy-preserving techniques to mask the gradients (Hardy et al. 2017). The encrypted gradients are then sent to the server, which sums them and returns the aggregated result to all clients. Each client uses the decrypted aggregated gradient to update their local model, ensuring that the final model parameters are shared across all clients without compromising the privacy of their individual datasets (Dai et al. 2021; Gu et al. 2020).

VFed-ML for Wastewater Treatment Process

This study aims to use VFed-ML to develop a unified model for securely and efficiently predicting energy consumption in wastewater treatment using multi-source data. In this context, the Melbourne WWTP can collaborate with other institutions to improve the accuracy of energy consumption predictions. For instance, one institution might have access to wastewater-related parameters, while another might hold climate-related data. By utilizing VFed-ML, these institutions can collaboratively develop a predictive model without needing to share their raw data. This approach not only preserves data privacy but also leads to more accurate predictions and customized treatment plans, ultimately optimizing the overall efficiency and effectiveness of the wastewater treatment process.

Description of Client and Server Models:

- *Client 1*: This predictive model is developed using operational data from WWTPs to predict energy consumption. It focuses on key parameters related to wastewater, such as Ammonia (Am), Total Nitrogen (Tnit), Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and the month.
- *Client 2*: This predictive model is designed to predict energy consumption based on key climate parameters. These include Minimum Temperature (Tmin),

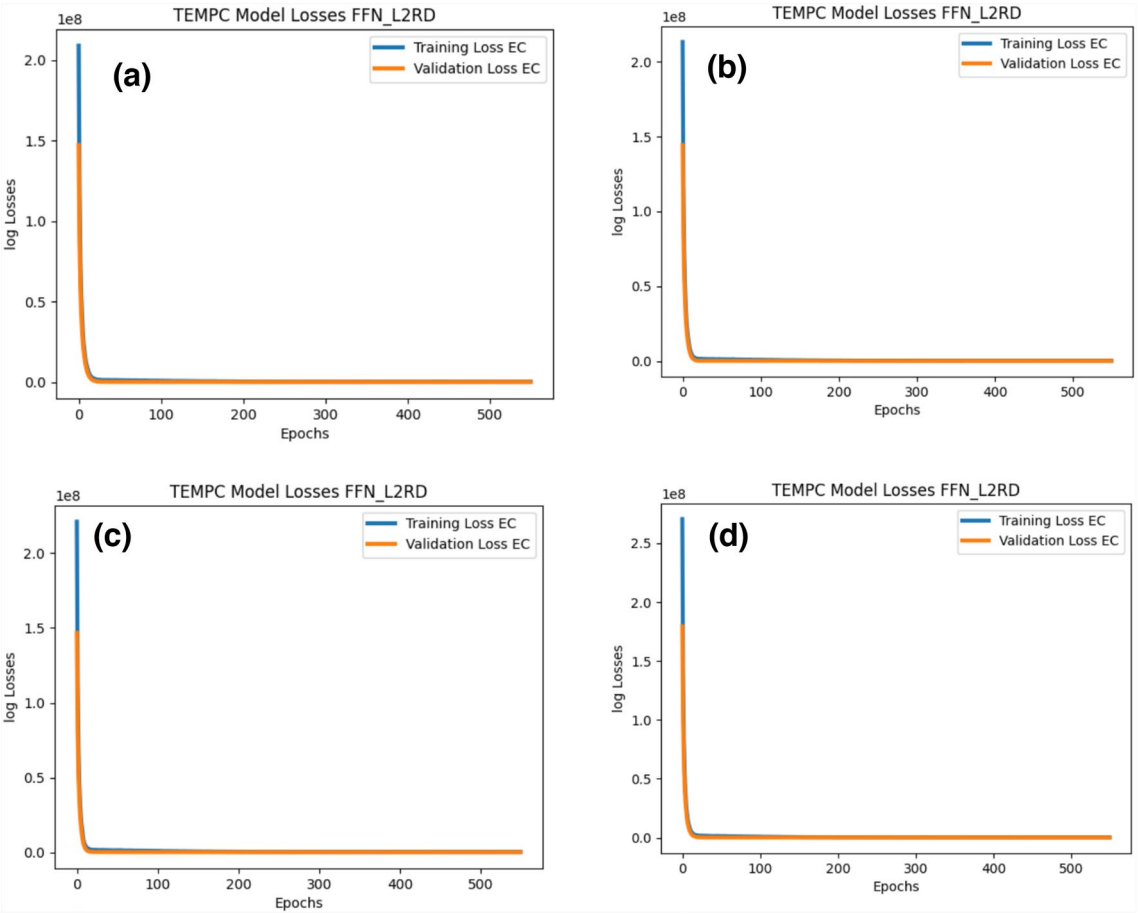

Fig. 19 **a** Client 2: Temperature related variables at round 1. **b** Client 2: Temperature related variables at round 2. **c** Client 2: Temperature related variables at round 5. **d** Client 2: Temperature related variables at round 10

Maximum Temperature (Tmax), average Temperature (Tavg), average relative Humidity (H), and the month.

- *Client 3*: This predictive model aims to predict energy consumption based on key atmospheric conditions. It includes parameters such as Atmospheric Pressure (AP), Precipitation (PP), average Visibility (VIS), Maximum Wind Speed (WSmax), average Wind Speed (WSavg), and the month.
- *Client 4*: This predictive model focuses on predicting energy consumption based on inflow and outflow parameters, including average Inflow, average Outflow, total Rainfall (PP), and the month
- *A central server* created is responsible for coordinating the federated learning process. It receives model updates from clients, aggregates these updates, and disseminates the global model back to the clients. Custom logic is used to evaluate the model's performance after each round and aggregate the metrics based on the number of examples used by each client. The core strategy of the server is Federated Averaging, which averages the model updates from different clients to update the global model.

Training Procedure: VFed-ML is employed to train Client 1 through Client 4 on local data collected from WWTPs while preserving data privacy. The training procedure involves the following steps:

1. Initialization: All four clients are initialized with random weights.
2. Client Training: Each WWTP client trains its local model using its operational data, ensuring that sensitive data remains within the respective WWTP.
3. Model Update Exchange: After local training, each WWTP transfers its model updates (e.g., gradients) to the central server.
4. Aggregation: The central server sums up the model updates that it received from all WWTPs to compute a global update.
5. Global Model Update: The global update is applied to all four clients to refine their parameters.
6. Iterative Training: Steps 2–5 are repeated iteratively for a predefined number of rounds, allowing all clients

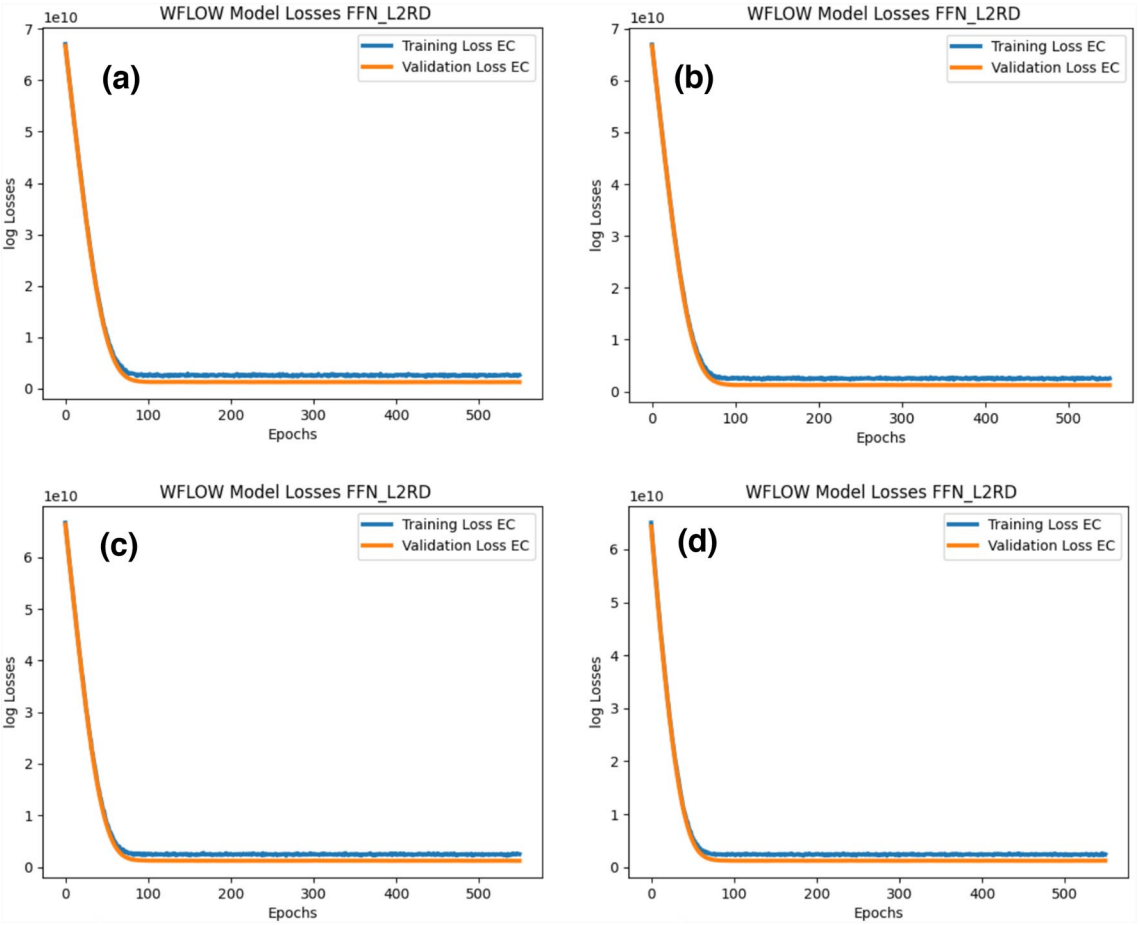

Fig. 20 **a** Client 3: Water flow related variables at round 1. **b** Client 3: Water flow related variables at round 2. **c** Client 3: Water flow related variables at round 5. **d** Client 3: Water flow related variables at round 10

to learn from the collective knowledge of all WWTPs while maintaining data privacy.

Client and Server Configuration:

- *Client Setup*: Each WWTP acts as a client in the federated learning setup. Clients are configured to run recurrent neural networks using Keras library in the Flower framework as shown in Fig. 16. It should be noted here that, not necessarily each model must use the same ML algorithms, it may differ from client to client. However, their neural network architecture must be the same. ML algorithms are responsible for training local models on their respective data, generating model updates based on local training and transmitting model updates to the central server for aggregation.
- *Server Setup*: A central server script sets up a federated learning server using the Flower framework as presented in Fig. 17. This server coordinates the federated learning process and is responsible for receiving model updates from clients, aggregating model updates using federated averaging, updating the global model parameters and disseminating the updated global model back to the clients for further training iterations.

The model's performance is evaluated after each round by averaging error metrics, based on the number of examples each client used. The `weighted_average` function computes the weighted Mean Absolute Error (MAE) by aggregating metrics from multiple clients based on their dataset size. This ensures more accurate overall evaluation. Federated Averaging (FedAvg) is employed as the learning strategy, using custom evaluation and metric aggregation functions. The server is started with fl.server.start_server, which listens to the local machine on 0.0.0.0:8080 and runs for 10 rounds. Careful configuration of clients and server, optimized training parameters, and proper data preprocessing

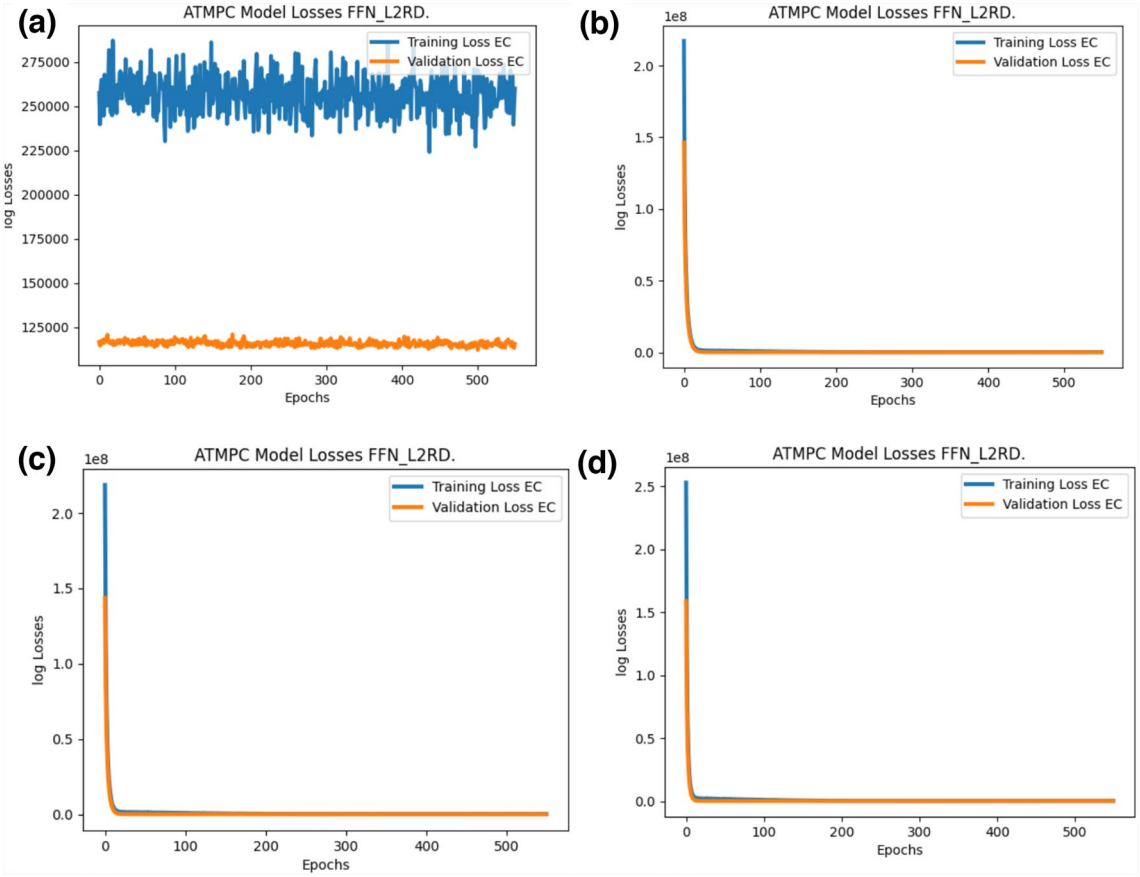

Fig. 21 **a** Client 4: Atmospheric related variables at round 1. **b** Client 4: Atmospheric related variables at round 2. **c** Client 4: Atmospheric related variables at round 5. **d** Client 4: Atmospheric related variables at round 10

in the VFed-ML framework ensure efficient and effective training of predictive models for WWTP.

Results and Discussions

The convergence behavior of VFed-ML is analyzed by tracking training and validation loss over epochs, as shown in Figs. 18, 19, 20 and 21. These plots illustrate each client's learning progress during each server round, helping assess model stability and training progress.

In the initial round of server execution, communication was established between Client 1 and Client 4. This round showed the signs of overfitting as presented in Fig. 18a and 21a. However, as subsequent rounds progressed, and Clients 2 and 3 joined the communication with the server, the model's performance improved. The server aggregated the weights received from each client and redistributed the updated weights back to them, resulting in a gradual improvement in prediction performance and a reduction in overfitting by the final rounds (Figs. 18d and 21d). The overall behavior of the proposed VFed-ML algorithms for predicting energy consumption in WWTPs was assessed by evaluating over 10 rounds. The decreasing trend in loss was observed, suggesting that the model was learning effectively.

The predictive relationships observed between EC and operational parameters such as COD, BOD, Tnit, Mean Temp. can be interpreted through the lens of WWTP processes. For instance, higher COD and BOD levels typically indicate a greater organic load in the influent, which requires increased aeration and chemical dosing to meet effluent quality standards, both are energy-intensive operations. Similarly, higher Tnit levels may necessitate enhanced nitrification and denitrification processes, which again contribute to higher energy demands. Mean Temp also plays a critical role in microbial activity and process kinetics. For example, higher temperatures can improve biological reaction rates, potentially reducing the required aeration time and energy input, while lower temperatures may slow microbial metabolism, thus demanding longer retention times and greater energy use. These interdependencies highlight how various biological and environmental factors can influence energy consumption in WWTPs.

Once the training and validation phases of the VFed-ML model are completed, predicting future energy consumption becomes a straightforward process. The trained model

simply requires updated measurements of the selected input parameters from the WWTP to predict EC. The use of these parameters does not necessitate any operational adjustments that might compromise treatment quality. The proposed federated machine learning framework enables WWTP operators to proactively plan and adjust operations for energy optimization. For instance, if the model predicts a spike in EC based on expected increases in organic or nutrient loads, operators can implement energy-saving strategies such as load balancing, adjusting aeration schedules, or optimizing chemical usage. In this way, the model serves not just as a prediction tool but also acts as a practical decision-support system that helps operators maintain energy efficiency.

Based on the success of the results from this article, the proposed VFed-ML approach also offers significant practical relevance in hydrological science, where access to diverse datasets is critical for building accurate predictive models. In many hydrological applications, such as water quality prediction, streamflow forecasting, and wastewater treatment optimization, data is often distributed across different institutions, regions, and monitoring stations. However, concerns over data privacy, ownership, and regulatory restrictions frequently hinder centralized data sharing. As a result, the proposed decentralized VFed-ML framework offers strong potential to collaboratively train models without requiring direct data exchange, preserving the integrity and security of sensitive data.

Conclusion

This study establishes a Vertical Federated Machine Learning (VFed-ML) framework to predict energy consumption in wastewater treatment plants (WWTPs) using real data from a Melbourne-based WWTP. Initially, various machine learning (ML) models such as ensemble learning methods, regression models, decision trees, and artificial neural networks (ANNs) are assessed. Feature selection techniques were applied to select the most important input features in the dataset. The results indicated that incorporating historical data specifically using time-lagged measurements significantly improved the accuracy of EC predictions. Some key findings from this work and recommendations for future research are listed as:

- A combination of diverse evaluation metrics and ML models were implemented to optimize energy consumption predictions in WWTPs. After testing several models, the most suitable one for the VFed-ML framework was identified.
- The VFed-ML's performance was compared to that of traditional models trained using centralized data integration. The study shows that this framework can be adapted to other WWTPs by adding relevant variables and plant-specific data.
- A notable aspect of the research is its approach to interagency data fusion, which increases the sample size and data dimensionality. This method supports big data applications and fosters the development of high-precision models, enhancing social and environmental value through better data services.
- The knowledge gathered from this paper can be used as a valuable reference for other WWTPs looking to enhance their EC prediction models and improve their understanding and management of energy usage.

Considerations for future research:

- Even after using variable selection techniques to optimize the model, predictions may still be improved by adding more variables that were excluded. Future research should explore a broader range of factors, such as operational parameters, influent characteristics, process conditions, and regulatory changes to enhance the performance of EC prediction models.
- Future work should focus on validating the model's feasibility in real-world settings, considering factors like operational constraints and computational requirements typically encountered in WWTPs.
- The limitations and challenges encountered during the simulations such as data heterogeneity, communication bottlenecks, and model convergence issues are acknowledged. To address these challenges and extend the scope of the study, future work will focus on incorporating additional features, exploring alternative federated learning algorithms, and validating the models using real-world datasets.
- The applicability of the proposed VFed-ML framework can be extended to various problems in science and engineering, including hydrological science, environmental monitoring, smart grid management, healthcare analytics, and intelligent transportation systems, where data privacy and decentralized learning are critical.

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Data Availability Some or all data that support this study's findings are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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