A hybrid AI model for forecasting electricity volume to optimize water supply company efficiency

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Abstract— **Most water supply companies consume a large amount of electricity to ensure technological processes of water purification and distribution. However, even though Vodokanals are a large consumer of electricity, the forecasting of electricity consumption is still not given priority. An accurate forecast of the amount of electricity consumption will allow optimization of the distribution of consumption, reducing the values of peak consumption and in general reducing the electricity costs. In this study, deep learning methods are proposed to predict the daily electrical load during a month. Where the performance of deep learning artificial neural networks and hybrid neural networks are compared, this study, based on the comparison of various deep learning methods, proposes to increase the effectiveness of the application of artificial neural networks by their hybridization, to forecast the daily electrical load in the monthly period. We combined the gray wolf optimizer (GWO) and the group data processing method (GMDH) to predict the optimal amount of electrical load in water utilities. Keywords—extrapolation; forecasting; observation data; plotting position formulas; uncertainty.**

Keywords— power consumption forecasting, deep learning, gray wolf optimizer, artificial neural networks, GMDH-GWO.

I. Introduction

Electricity load forecasting is a critically important task for water supply companies, as it will allow developing measures to increase the stability of the electricity supply system, economic efficiency, and reliability of water supply. More accurate forecasting makes it possible to optimize the use of energy resources, predict the need for backup power, and ultimately reduce the man-made load on the natural environment. With demand forecasting, generators can produce optimal power levels and save energy resources, and utilities get enough time to develop and implement plans to balance electricity consumption and ensure the functioning of related systems.

Water utilities with an energy management policy in place consume less energy than similar utilities without one [7] but many water utilities still do not have such a policy. Given the changing energy landscape, having a guiding set of energy principles is now more important than ever. Water utilities may benefit from additional research on the type, scope, and effectiveness of energy management policies specific to them, as well as best practice recommendations for developing and adopting such policies for their unique circumstances [8].

Energy management at the water utility level faces a major challenge in obtaining the necessary information. Water utilities struggle to track basic energy usage data, even on a monthly or yearly basis. While these utilities already monitor pressure, flow, and water quality at multiple sites with intervals of less than an hour, it's equally important for them to extend this practice to energy monitoring [8]. In the future, water utilities need to be just as proficient in processing energy data as they are in processing water data. As energy transactions become more dynamic and digital, the water sector must intensify its efforts to effectively manage relevant data to its advantage.

Forecasting electricity consumption accurately is challenging due to various influencing factors, such as population, economic development, electricity infrastructure, and climatic conditions. Many studies have been conducted to develop power consumption forecasting models, which are generally classified into three categories: nonlinear intelligent models, statistical analysis models, and gray forecasting models.

Just as energy can be saved by optimally scheduling pumps, energy can be saved by optimally distributing water sources. For large water supply systems with several interchangeable water sources, one of the simple but underused methods is source selection [8].

The category of nonlinear models mainly includes techniques such as artificial neural networks and support vector machines. For instance, Bouzerdoum et al. [16] introduced an innovative approach for short-term PV power forecasting by combining SARIMA and SVM models. This hybrid model demonstrates exceptional accuracy, surpassing individual SARIMA and SVM models, and effectively estimates small-scale power generation without depending on forecasted meteorological parameters. However, its accuracy relies on having sufficient training data and experience.

The Universal Approximation Theorem asserts that an Artificial Neural Network (ANN) can effectively approximate any nonlinear function. ANN models have been utilized for forecasting electricity demand since the 1990s and have consistently shown promising results [5, 6]. Recent advancements in computing power and cutting-edge algorithms have led to the development of neural networks using machine learning techniques, particularly deep neural networks (DNN), which have become one of the primary methods for forecasting electricity demand. This has been made possible by enhancing the abstraction capabilities of model functions. The ability of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, which are based on Recurrent Neural Networks (RNN), to handle sequential data and long-term dependencies during the extraction of complex patterns in data has significantly contributed to their popularity among researchers [5, 6].

The research community is increasingly focusing on hybrid methods to improve energy modeling. These methods combine different approaches or strategies, using the strengths of each to improve the accuracy and efficiency of energy models. Additionally, the researchers applied metaheuristic techniques, which include sophisticated intelligent algorithms, to fine-tune the parameters of these models, optimizing them for superior results. This synergy of hybrid and AI-based methodologies paves the way for advancements in energy modeling. Heirkha et al. developed a novel algorithm that integrates artificial neural networks (ANN), principal component analysis (PCA), data envelopment analysis (DEA), and ANOVA methods to estimate and forecast electricity demand. This algorithm considered seasonal and monthly variations, using pre-processing and post-processing to improve the performance of the ANN model. The effectiveness of this approach was demonstrated using electricity consumption data in Iran, which produced accurate estimates.

In this study, for the first time, it is proposed to combine the gray wolf optimizer (GWO) and the group data processing method (GMDH) to predict the optimal amount of electrical load in water supply companies. The use of these methods allows you to automate the modeling process, optimize the model structure, and ensure high accuracy of forecasting, considering complex, non-linear dependencies.

II. Materials and methods

A. Description of the process of electricity consumption by pumping stations and preparation of data for modeling

Pumping stations in water supply companies are the main components that ensure the transportation of water from water intake sources (rivers, reservoirs, wells, etc.) to consumers through the pipeline system. They differ in types, power, productivity, and specifics of use, depending on the needs and features of the water supply system.

The most common types of pumps in water supply companies are:

- Centrifugal pumps are the most common due to their reliability, ability to work at high speeds, and provide a large flow of water. They are used to supply large volumes of water from water intakes to consumers through a network of pipelines.
- Piston pumps are used to supply water under high pressure, in high-pressure systems, in high-rise buildings. They are often used to transport water to high-rise buildings or to supply water to systems with high resistance.
- Rotary pumps are used in specific cases, for example, for raising water from underground wells.

Pump performance (m^3/h) determines the volume of water that the pump can pump per unit of time. Power (kW) determines the amount of electricity required to operate the pump. The power depends on the height of the water rise (pressure) and the volume of water that is pumped.

Pumps are often equipped with frequency converters, which allow you to adjust their speed according to the needs of the system. This ensures flexible management and more efficient use of energy. Modern systems often have automated control systems (SCADA), which allow you to monitor the condition of the pumps and quickly respond to changes in the load or malfunctions.

Most of the energy is used to pump water, overcome the hydraulic resistance of pipelines, and lift the water to the necessary height. The pump consumes more energy when lifting water to greater heights or over longer distances. Additionally, some water systems require energy to filter, clean, and treat water before it is supplied to consumers.

By predicting water consumption, pumps can be adjusted by reducing their power during low consumption or peak loads. This reduces electricity costs and reduces the load on electrical networks. The use of water storage tanks also allows water to be stored during periods of low demand and reduces the load on pumps during periods of peak consumption.

In this study, we used data on electricity consumption by pumping stations for water distribution problems over the past five years. Using machine learning methods (cluster analysis), they were divided into groups of high consumption, moderate consumption, and abnormal consumption. Further simulation results are described in the following sections.

An example of the distribution of electricity consumption by the water supply company over the past five years (for security reasons, we do not specify the name) into cluster groups is shown in Figure 1.

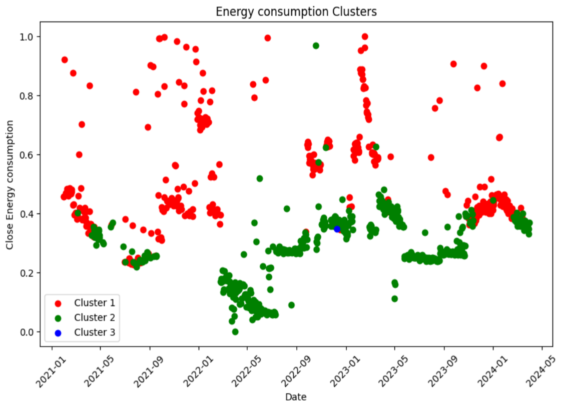

Figure 1. Division into clusters of electricity consumption groups by the water supply company

In Figure 1, the electricity consumption by the water supply company is divided into three clusters, where the first group of clusters indicates a high volume of consumption, the second group of clusters indicates a moderate volume, and the third group indicates anomalies in the consumption of electricity to pump the required volume of water. The dynamics of electricity consumption by month is shown in Figure 2.

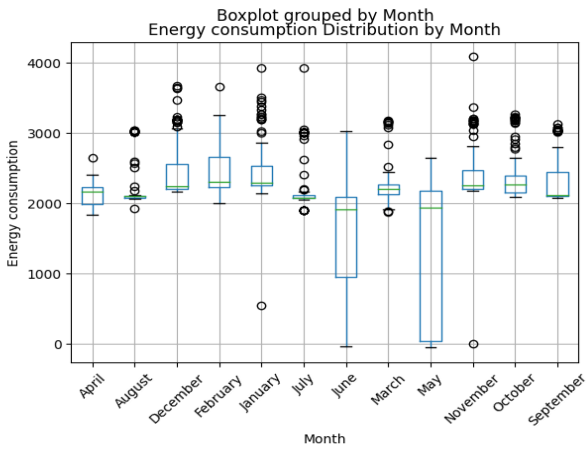

Figure 2. An example of electricity consumption by a water supply company

B. *Gray Wolf Optimization Algorithm (GWO)*

The GWO method is a metaheuristic algorithm inspired by the life of gray wolves, which simulates the leadership hierarchy and how gray wolves hunt in the wild. The leadership hierarchy is divided into four groups of wolves; alpha provides the first most acceptable solution, beta provides the second most acceptable solution, delta provides the third most acceptable solution, and finally, omega provides the remaining available solutions [15].

The gray wolf algorithm is divided into three stages: searching for prey (Equation 1), surrounding prey (Equation 2), attacking prey.

Search for prey (reconnaissance). Gray wolves look for solutions near the alpha, beta, and delta positions. Mirjalili and others. (2014), use A with random values greater than 1 or less than −1 to force gray wolves to disperse and improve exploration to allow the algorithm to perform a global search in the search space.

Prey environment. At this step, the prey is surrounded by a pack of gray wolves. The mathematical model of the prey environment is described below (formulas 1 - 2) [15].

$$\vec{D} = |\vec{C} \cdot \overrightarrow{X_p}(t) - \vec{X}(t)| \quad (1,1)$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A} \cdot \vec{D} \quad (1,2)$$

where, t is the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\overrightarrow{X_p}$ the vector of the position of the victim, $\vec{X}$ is the vector of the position of the gray wolf. Vectors $\vec{A}$ and $\vec{C}$ are determined using the following equations [15]:

$$\vec{A} = \overrightarrow{2a} \cdot \overrightarrow{r_1} - \vec{a} \quad (1,3)$$

$$\vec{C} = 2 \cdot \overrightarrow{r_2} \quad (1,4)$$

where, a linearly decreases from 2 to 0 during iterations of the algorithm. r_1, r_2 are random vectors in the interval [0, 1].

Hunting. Alpha (α), beta (β), and delta (δ) wolves participate in the hunting process, with alpha (α) representing the best solution in the pack, beta (β) the second best solution, and delta (δ) the third best solution. The first three best solutions are kept and the other wolves update their current positions randomly in the search space. The behavior of wolves is modeled using the following equations [15]:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \quad (2,1)$$

$$\vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \quad (2,2)$$

$$\vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \quad (2,3)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha) \quad (2,4)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta) \quad (2,5)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \quad (2,6)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (2,7)$$

where, $\vec{X}_1, \vec{X}_2, \vec{X}_3$, represent the alpha (α), beta (β) and delta (δ) positions of the wolf, $\vec{X}(t+1)$ is the updated next position of the wolf. $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ are the first three best solutions [15].

Prey attack. The hunting process of gray wolves ends when the prey stops moving.

The current study begins by using the GWO method to solve an optimization model for energy consumption forecasting accuracy. The GWO algorithm is then used to determine the best weights for prediction algorithms and to predict the amount of test data. After that, the prediction accuracy indicators of the GWO algorithm are calculated [15].

C. *Forecasting the optimal amount of electrical load based on time series forecasting*

The Group Data Processing Method (GMDH) is a self-organized learning technique that enables you to manage the process of a complex model from the input set to the output data and determine the model's parameters. The GMDH network creates a connection between the input and the output, which is referred to as a series of Volterra functions or a function of the Kolmogorov–Gabor polynomial [12, 13].

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m} \sum_{j=1}^{m} a_i x_i x_j + + \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{m} a_{ijk} x_i x_j x_k + \cdots \quad (3)$$

Group GMDH transforms neurons into more complex units with polynomial transfer functions and simplifies the communication between neurons while developing automatic algorithms for structure design and weight adjustment [12].

In the process of creating and evaluating the model, the data were divided into three sets: a training set, a test set, and a verification set. The training set is included in the construction of the model, and the verification set is used for the selection of neurons. The unobserved data is used to test the performance of the model using the test set. The GMDH neural network method is a hierarchical system consisting of neurons. The number of relevant neurons in each layer depends on the number of inputs [12].

To train this type of ANN, we divided the data on electricity consumption into three sets: training, testing, and verification. A model was created based on the training set. Polynomial transfer functions allowed us to take into account nonlinear relationships between input parameters: volume of consumption, time, and volume of water pumping. The validation data set was used to test the accuracy of the predictions and select the best neurons. The algorithm automatically added or removed neurons, depending on their efficiency, to ensure the optimal structure of the model.

After building a model with the optimal number of neurons, this model was used to predict the optimal amount of electrical load. This method is effective for water supply companies, as it takes into account the complex and changing relationships between factors affecting electricity consumption and allows the model to be adapted in real-time for more accurate forecasting.

Since electricity consumption in water utilities may vary based on the season or other conditions, GMDH can be set to update periodically with new data, increasing its adaptability and long-term accuracy.

D. *Assessment of accuracy of forecasting models*

The study used the MAPE and RMSE accuracy assessment metrics to evaluate the forecasting accuracy of hybrid models. Formula (4) presents the root mean square error (RMSE) formula, which defines RMSE as the standard deviation of the difference between the actual value and the predicted value of the data [13].

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{x}_i - x_i)^2}{n}} \quad (4)$$

Where $\hat{x}_i$ is the predicted volume of test data, x_i denotes the actual volume of test data, and n is the number of test data [13].

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{x}_i - x_i}{x_i} \right| \quad (5)$$

The MAPE index (equation (5)) measures the difference between the predicted and actual values for test data. Another index used in this study for prediction algorithms is the mean absolute error (MAE), which indicates the absolute difference between the predicted and actual test data for energy consumption [13].

In this study, we focus on minimizing the Mean Absolute Percentage Error (MAPE) value. The training results of the hybrid models used for forecasting power demand are inputted into the optimization model. The proposed model calculates a new prediction value by assigning weights to each algorithm and to their predictions. It also considers the intercept value and the difference between the predicted and actual data. The model then recommends the optimal MAPE index state. The MAPE optimization model is presented in [13].

III. Simulation results

A. *The result of training the GMDH model*

The group data processing method (GMDH) is an effective forecasting method. This method analyzes complex relationships between variables. In the case of forecasting the amount of electricity consumption in water supply companies, this method allows for taking into account a wide range of factors that affect energy consumption, such as weather conditions, daily and seasonal fluctuations, the level of water demand, etc.

As a result of training the group data processing model, we obtained the following results: the GMDH model is built from 19 layers, each of which is trained separately. The training time of each layer varies from about 8.87 seconds (layer 0) to 20.70 seconds (layer 2), indicating the speed and efficiency of the model-building process.

From layer 1 to layer 18, the training time is stable and fluctuates between 18-21 seconds, which shows that the model is stable when adding new layers and optimizing. The RMSE model accuracy indicator indicates the average difference between the predicted and actual values. A smaller RMSE value indicates higher accuracy. The RMSE value on the test data (245.21) is lower than on the training data (379.99), which may indicate that the model generalizes the data well and is not overtrained.

A low MSE value for the test data indicates a good adaptation of the model to the new data. MAPE shows the mean absolute error as a percentage of the actual values. The values of 5.899% for the training data and 0.0529% for the test data indicate that the model predicts power consumption well. A significantly lower MAPE value on the test data may indicate that the model fits the new data very well. The result of training the GMDH model is shown in Figure 3.

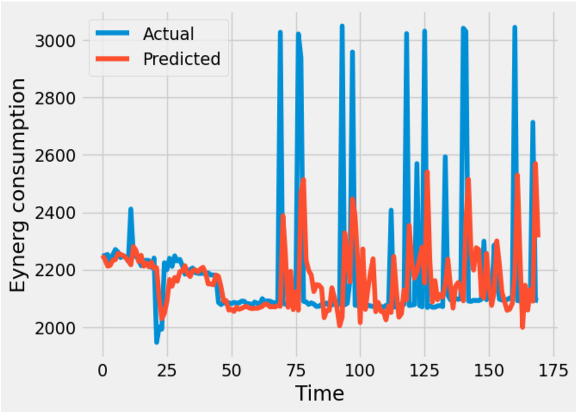

Figure 3. An example of electricity consumption by a water supply company

B. The result of hybrid GMDH-GWO training

The GWO algorithm was used to optimize the parameters of the GMDH model, in particular the number of layers and the type of activation functions. This made it possible to automatically adjust the model, ensuring high accuracy without manual selection of parameters. The GMDH network adapted to non-linear dependencies in the data, which was very useful for forecasting complex time series such as electricity consumption. The combination with GWO made it possible to choose the best structure, ensuring the adaptability of the model to changes in the data. The result of training the GMDH-GWO hybrid model is shown in Figure 4.

By optimizing the model using GWO, the root mean square error (RMSE) and mean absolute percentage deviation (MAPE) were significantly reduced. This has provided more accurate forecasts, allowing for more efficient resource management and lower energy costs.

The combination of Grey Wolf Optimizer (GWO) and Group Method of Data Handling (GMDH) enabled automatic selection of model parameters, reducing the need for expert intervention in tuning and ensuring more efficient use of computing resources.

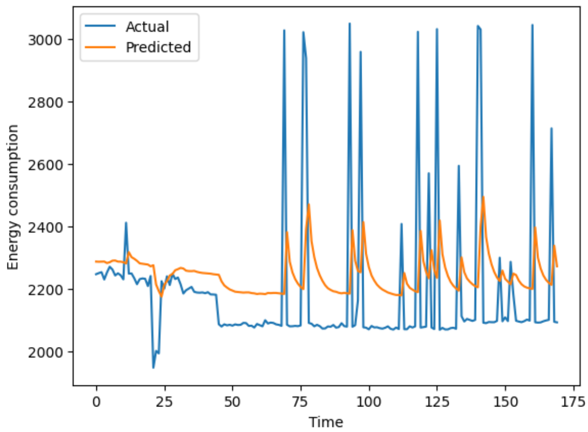

Figure 4. The result of the hybrid GMDH-GWO method simulation

Visualization of forecasts showed that the model can accurately reproduce trends and fluctuations in electricity consumption, which is critically important for water supply companies when planning energy resources.

C. Comparison of the obtained results and assessment of the accuracy of hybrid models

The training results of the GMDH model show that the model has better performance on the training data set than the GMDH-GWO hybrid model. In the GMDH neural network, each layer was trained for an average of about 19-20 seconds, while in the hybrid model, the training time is slightly longer. GMDH-GWO has a lower RMSE on the training set, indicating better accuracy on the training data. Similarly, the MSE of the GMDH-GWO model is lower, confirming the smaller mean error. MAPE in the GMDH-GWO network is 5.90%, in the GMDH model - 6.72%. This indicates that the batch data processing method model is more accurate during training. RMSE on the test set for both models is almost the same, with a slight advantage of the second set. This shows that both models have similar accuracy on new, unobserved data. The MSEs of both models are also close, with the second set having slightly lower values, but the difference is small.

The first set has higher accuracy and lower error rates compared to the training set, indicating its superior ability to learn patterns in the data. Both sets perform similarly on the test set, but the first set has a lower MAPE, suggesting better generalization ability. Overall, the first set is more optimal because it demonstrates superior results on both training and test data.

D. Forecasting the optimal amount of electricity for the tasks of Vodokanals

Forecasting the optimal electrical load is important for water utilities for several reasons:

- Economic efficiency: Knowing when and how much electricity will be needed allows companies to optimize energy costs. This helps avoid overspending during peak loads or inefficient use of energy during periods of low demand.
- Maintaining system stability: Load forecasting allows for a stable water supply, as water pumping stations and other components of the water supply system require electricity to operate. This allows you to avoid emergencies and water supply failures.
- Optimizing equipment operation: Companies can schedule the operation of pumping stations and other equipment based on predicted load, which minimizes wear and tear and extends the life of the equipment.
- Environmental component: Optimizing electricity consumption helps reduce CO_2 emissions and other harmful emissions associated with electricity production, which is important for companies seeking to reduce their impact on the environment.
- Backup power planning: Load forecasting allows you to prepare for possible power

outages and properly plan the use of backup power sources, which will ensure an uninterrupted water supply.

Therefore, the forecasting of electrical load is critically important for ensuring the economic, technical, and environmental efficiency of water supply companies.

IV. Conclusion

This study investigates the importance and effectiveness of combining Grey Wolf Optimizer (GWO) and Group Method of Data Handling (GMDH) for forecasting electricity load in water supply systems. It demonstrates the practical value of these methods in enhancing the performance of such companies. GMDH constructs a model using a training dataset by applying polynomial transfer functions to the neurons, enabling the consideration of non-linear dependencies between inputs. The network structure is optimized automatically using a verification set to select the most efficient neurons in each model layer. The model is then tested on non-training data to assess its performance and accuracy.

The idea of combining GWO and GMDH to predict the optimal electrical load in water distribution problems provides the following advantages:

- Improved Forecasting Accuracy: The combination of Grey Wolf Optimizer (GWO) and Group Method of Data Handling (GMDH) has enabled the creation of models with high forecasting accuracy by optimizing weights and capturing nonlinear relationships. This is particularly valuable for forecasting complex and non-linear systems, like electricity consumption in water supply companies, where numerous factors such as weather conditions and consumer demand need to be considered.
- Rapid adaptation to changes: The use of GWO allowed GMDH parameters to be adaptively changed in case of new data or changing conditions. This made it possible to create models that quickly adapt to new circumstances and provide accurate real-time forecasting.
- The combination of Grey Wolf Optimization (GWO) with Group Method of Data Handling (GMDH) has automated the process of finding the optimal model. This has reduced the time and effort required for model development. As a result, more accurate forecasts can be obtained faster, leading to more effective resource management.

Hence, it is crucial to combine the Gray Wolf Optimizer with the GMDH model to enhance forecasting accuracy. GWO efficiently optimizes the parameters and structure of the GMDH, thereby reducing the risk of overtraining and ensuring the model's adaptability.

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