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A Hybrid Artificial Neural Network–Genetic Algorithm Framework for Intelligent Energy Management in Water Pumping Stations

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Abstract: -Drinking water pumping stations are among the largest energy consumers in water distribution systems, where inefficient pump scheduling often leads to excessive electricity consumption and increased operational costs. This paper proposes a hybrid Artificial Neural Network–Genetic Algorithm (ANN–GA) intelligent energy management framework for optimizing the operation of water pumping stations while satisfying hydraulic and operational constraints. The proposed framework consists of two complementary modules. The first module employs an Artificial Neural Network (ANN) to accurately forecast short-term water demand based on historical consumption patterns, thereby providing reliable predictions for proactive pump scheduling. The second module utilizes a Genetic Algorithm (GA) to determine the optimal pump operating schedule by minimizing electricity consumption while maintaining the required water level in the storage tank and ensuring compliance with system operating constraints. The optimization process considers both the predicted water demand and the hydraulic characteristics of the pumping system, allowing the management strategy to adapt dynamically to changing demand conditions. The proposed approach was evaluated through simulation under realistic operating conditions and compared with a conventional pumping management strategy. The obtained results demonstrate the effectiveness and robustness of the hybrid ANN–GA framework, achieving energy savings of up to 39.4% over a single day of operation without compromising the reliability of water supply. These findings highlight the potential of combining machine learning and evolutionary optimization techniques to enhance energy efficiency, operational performance, and sustainability of smart water distribution systems.

Keywords: Energy optimization; water pumping stations; artificial neural networks (ANN); genetic algorithms (GA); water demand forecasting; pump scheduling; energy efficiency; smart water management.

1. Introduction

The energy consumed by pumping systems represents approximately 20% of global electricity consumption, and a significant portion of this energy is lost due to inefficient management during the operational phase [1], [2]. Optimizing energy use in water pumping systems therefore offers considerable potential to reduce consumption, while providing economic, technical, and environmental benefits.

The optimization of water pumping systems has attracted considerable research attention over the past decades. Early approaches mainly relied on statistical forecasting techniques such as autoregressive integrated moving average (ARIMA) models and seasonal regression, which provided reasonable short-term predictions but often failed to capture the nonlinear and highly dynamic variations in water demand [3]. To overcome these limitations, artificial intelligence methods have been introduced, with Artificial Neural Networks (ANNs) emerging as one of the most effective tools for water demand forecasting thanks to their ability to model nonlinear relationships and adapt to fluctuating consumption patterns [4], [5]. More advanced methods, including support vector machines, deep learning models such as Long Short-Term Memory (LSTM) networks, and hybrid approaches combining signal decomposition with ANN, have further improved forecast accuracy [6], [7].

In parallel, research on pump scheduling optimization has evolved from classical mathematical programming techniques, such as mixed-integer linear and nonlinear programming [8], towards metaheuristic algorithms better suited for the nonlinear and nonconvex nature of hydraulic systems. Among these, Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) have been widely used, offering robustness, scalability, and improved performance in minimizing operational costs and energy use [9], [10]. Hybrid frameworks combining ANN-based demand forecasting with optimization algorithms have demonstrated significant energy savings, with reductions ranging from 15% to 40% compared to traditional rule-based methods [11], [12].

Recent studies have also explored Mult objective optimization, integrating objectives such as pump wear reduction, leakage control, and pressure management [13], as well as advanced strategies like Model Predictive Control (MPC) and Reinforcement Learning (RL) to dynamically adjust pump operations in real time [14], [15], [16]. Despite these advances, several research gaps remain, including robustness to forecast uncertainty, model generalizability across utilities, and integration into SCADA systems.

In response to these challenges, we developed the RNAG management tool, which combines ANN-based water demand forecasting with GA-based pump scheduling optimization. This hybrid approach enables sustainable and efficient operation of pumping systems while ensuring hydraulic constraints are respected, achieving energy savings of up to 39.4% per day. RNAG thus represents a practical and reliable solution for modern water utilities aiming to reduce energy consumption and enhance system performance [17].

2. Presentation of the studied pumping station

The studied pumping station consists of three centrifugal pumps, with two in operation and one reserved as a backup. These pumps supply a 1,500 m³ water storage tank (Fig. 1), which serves the western part of the city of Gabès. The operation and management of the pumping station are overseen by SONEDE (Société Nationale d'Exploitation et de Distribution des Eaux). The pumping system is controlled through a load-shedding strategy, where pumps are regulated based on the water level in the storage tank, ensuring reliable water supply while optimizing energy usage.

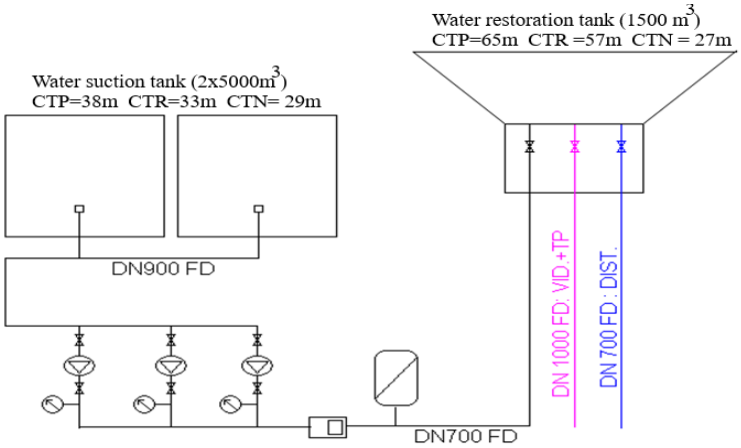


Figure 1. Pumping system diagram

3. Intelligent pumping management tool

The RNAG tool is based on genetic algorithms for the optimization part and the technique of artificial neural networks for consumption forecasting.

3.1. Demand forecasting model

3.1.1.Architecture of the ANN forecasting model

Accurate water demand forecasting is crucial for the efficient operation of pumping stations, as it enables better scheduling of pumps, reduces energy consumption, and minimizes operational costs. For this purpose, we

employed Artificial Neural Networks (ANNs), which are well-suited for capturing nonlinear relationships between water demand and influencing factors such as time, day, season, and previous consumption levels [18], [19].

The ANN model used in this study consists of three layers (Fig 2):

- **Input Layer:** Contains 44 neurons, representing the key variables affecting water consumption:
  - 12 neurons for the month to capture seasonal variations,
  - 7 neurons for the day of the week to account for weekly consumption patterns,
  - 24 neurons for the hour of the day to reflect daily fluctuations in water demand,
  - 1 neuron for the previous hour's water consumption to capture short-term dependencies.
- **Hidden Layer:** Processes the input signals through a set of nonlinear activation functions, allowing the network to learn complex patterns and interactions between the input variables. The number of hidden neurons was optimized through trial-and-error and cross-validation to balance model accuracy and computational efficiency.
- **Output Layer:** Provides the predicted water demand for the next hour, which serves as the primary input for the pump scheduling optimization algorithm.

The model is trained using historical consumption data, which are divided into training, validation, and testing sets to ensure that the ANN generalizes well to unseen conditions. During training, the weights of the neurons are adjusted using a backpropagation algorithm with a suitable learning rate, aiming to minimize the prediction error. By capturing both short-term and seasonal patterns, this ANN-based forecasting model provides accurate and reliable predictions of water demand, which are essential for optimal pump management and energy savings.

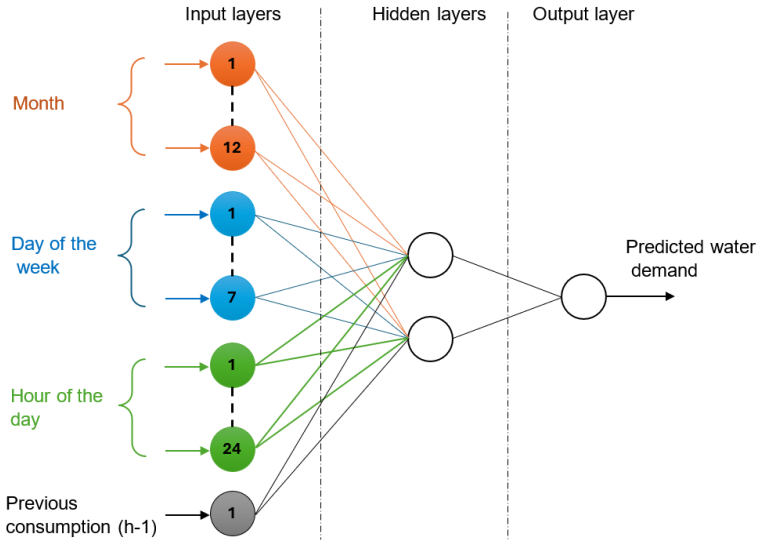


Figure 2. Structure of the artificial neural network model

3.1.2.Mathematical formulation of the ANN forecasting model

In this section, we will give the concise and formal mathematical description of the ANN we have described (44 inputs → 1 hidden layer → 1 output), including the forward pass, loss, training rule (backprop / gradient descent), regularization options and evaluation metrics.

➢ *Notation and input vector*

Let the dataset consist of N windows (hourly samples). For sample t define the input vector $x^{(t)} \in R^{44}$:

$$X^{(t)} = \left[m_1^{(t)}, \ldots, m_{12}^{(t)}, d_1^{(t)}, \ldots, d_7^{(t)}, h_1^{(t)}, \ldots, h_{24}^{(t)}, y^{(t-1)}\right]^T \quad (1)$$

Where:

$m_i^{(t)} \in \{0,1\}$: one-hot encoding of month (12 dims).

$d_j^{(t)} \in \{0,1\}$: one-hot encoding of day-of-week (7 dims).

$h_k^{(t)} \in \{0,1\}$: one-hot encoding of hour-of-day (24 dims).

$y^{(t-1)} \in R$: observed water consumption at previous hour (optionally normalized).

Target scalar: $y^{(t)}$ — actual consumption at next hour (to predict $\hat{y}^{(t)}$).

➢ *Network architecture and forward pass*

Let the hidden layer contain H neurons (selected by cross-validation). Denote:

Input-to-hidden weights: $\mathbf{W}^{(1)} \in R^{(H\times 44)}$

- Hidden bias: $\mathbf{b}^{(1)} \in R^H$
- Hidden activations (elementwise): $\phi(\cdot)$ (e.g., ReLU or tanh)
- Hidden-to-output weights: $\mathbf{W}^{(2)} \in R$ (column vector)
- Output bias: $\mathbf{b}^{(2)} \in R$
- Output activation : linear (regression)

Forward equations for sample t:

➢ *Linear transform to hidden:*

$$\boldsymbol{z}^{(t)} = W^{(1)}.x^{(t)} + b^{(1)} \qquad \in R^H \qquad (2)$$

➢ *Nonlinear activation (hidden layer):*

$$h^{(t)} = \emptyset\left(z^{(t)}\right) \qquad \in R^H \qquad (3)$$

Common choices:

- ReLU : $\phi(u) = max(0,u)$
- tanh : $\phi(u) = tanh(u)$
- Sigmoïd: $\phi(u) = \frac{1}{1+e^{-u}}$ (less common for hidden regression nets)

➢ *Output (prediction):*

$$\hat{y}^{(t)} = \left(W^{(2)}\right)^T.h^{(t)} + b^{(2)} \qquad \in R \qquad (4)$$

➢ *Loss function and regularization*

Use the Mean Squared Error (MSE) over a mini-batch or whole training set. For a batch $\mathcal{B}$:

$$\mathcal{L}_{MSE}(\Theta) = \frac{1}{|\mathcal{B}|}\sum_{t\in\mathcal{B}}\left(y^{(t)} - \hat{y}^{(t)}\right)^2 \qquad (5)$$

Add L_2 weight decay (ridge) to limit overfitting:

$$\mathcal{L}(\Theta) = \mathcal{L}_{MSE}(\Theta) + \lambda = \left(\left\|W^{(1)}\right\|_F^2 + \left\|w^{(2)}\right\|_2^2\right) \qquad (6)$$

where $\lambda \geq 0$ is the regularization coefficient and $\Theta = \{\boldsymbol{W}^{(1)}, \boldsymbol{b}^{(1)}, \boldsymbol{w}^{(2)}, b^{(1)}$ Dropout can also be included in the hidden layer during training as an alternative regularize.

➢ *Training: backpropagation + gradient descent (mini batch)*

Compute gradients of $\mathcal{L}$ w.r.t. parameters and update using (stochastic) gradient descent or an adaptive optimizer (Adam).

Backward pass (per sample or batch) sketch of gradients:

- *Output error :*

$$\delta_{out}^{(t)} = \frac{\partial \mathcal{L}}{\partial \hat{y}^{(t)}} = -2\left(y^{(t)} - \hat{y}^{(t)}\right) \quad (7)$$

- *Gradient w.r.t. output weights and bias (batch averaged):*

$$\nabla w^{(2)}\mathcal{L} = \frac{1}{|\mathcal{B}|}\sum_{t\in\mathcal{B}} \delta_{out}^{(t)} h^{(t)} + 2\lambda w^{(2)} \quad (8)$$

$$\nabla_{b^{(2)}}\mathcal{L} = \frac{1}{|\mathcal{B}|}\sum_{t\in\mathcal{B}} \delta_{out}^{(t)} \quad (9)$$

- *Backpropagate to hidden layer:*

$$\delta_{hidden}^{(t)} = \left(w^{(2)} \odot \delta_{out}^{(t)}\right) \odot \phi'\left(z^{(t)}\right) \quad (10)$$

where $\odot$ is elementwise product and $\phi'(\cdot)$ is derivative of activation.

- *Gradients w.r.t. $W^{(l)}$, $b^{(l)}$:*

$$\nabla w^{(1)}\mathcal{L} = \frac{1}{|\mathcal{B}|}\sum_{t\in\mathcal{B}} \delta_{hidden}^{(t)}\left(x^{(t)}\right)^T + 2\lambda w^{(1)} \quad (11)$$

$$\nabla_{b^{(1)}}\mathcal{L} = \frac{1}{|\mathcal{B}|}\sum_{t\in\mathcal{B}} \delta_{hidden}^{(t)} \quad (12)$$

- *Parameter update (gradient descent with learning rate η):*

$$W^{(1)} \leftarrow W^{(1)} - \eta\nabla_{W^{(1)}}\mathcal{L}, \quad W^{(2)} \leftarrow W^{(2)} - \eta\nabla_{W^{(2)}}\mathcal{L} \quad (13)$$

The same goes for biases. If you use Adam or RMSProp, you must replace it with the optimizer-specific update.

➢ *Model selection and training protocol*

- Data split: training / validation / test (e.g., 70% / 15% / 15%) with chronological split to avoid leakage.
- Hyperparameters to tune via cross-validation on validation set:
  - number of hidden neurons *H*,
  - learning rate η,
  - regularization coefficient λ,
  - batch size,
  - activation function and dropout rate.
- Early stopping: monitor validation loss and stop when it does not improve for *P* consecutive epochs (prevents overfitting).
- Normalization: standardize continuous inputs (previous hour consumption) using training set mean and std.

➢ *Performance metrics*

Report on regression metrics on test set:

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N_{test}}\sum_t \left(y^{(t)} - \hat{y}^{(t)}\right)^2} \quad (14)$$

- Mean Absolute Error (MAE):

$$MAE = \frac{1}{N_{test}} \sum_t \left| y^{(t)} - \hat{y}^{(t)} \right| \quad (15)$$

- Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100\%}{N_{test}} \sum_t \frac{|y^{(t)} - \hat{y}^{(t)}|}{\max(\varepsilon, y^{(t)})} \quad (16)$$

(use ε small to avoid division by zero)

- Coefficient of determination R^2:

$$R^2 = 1 - \frac{\sum_t (y^{(t)} - \hat{y}^{(t)})^2}{\sum_t (y^{(t)} - \bar{y})^2} \quad (17)$$

3.2. Optimization Model Using Genetic Algorithms (GA)

The Genetic Algorithm (GA) approach is one of the most effective techniques for solving combinatorial optimization problems, such as the one addressed in this study [20], [21]. Our optimization model begins by generating a population of n individuals, representing a candidate pump operation schedule over a 24-hour horizon. Each individual is then evaluated using a fitness function (Equation 1) to assess his performance with respect to the optimization objectives.

The population undergoes a series of genetic operations, including selection, crossover, and mutation, which produce a new generation while penalizing individuals that violate the optimization constraints (Equation 2).

This iterative process continues until the stopping criterion is satisfied. At the end of the algorithm, the optimal solution corresponds to the set of decision variables that minimize the objective function while respecting all system constraints imposed to ensure system feasibility:

Each individual is evaluated using the objective function, which seeks to minimize the total daily energy consumption of the pumping station:

$$\min f(x) = \sum_{t=1}^{t=t_f} \sum_{n=1}^{n_p} P_p(t,n).u(t,n) \quad (18)$$

$$\begin{cases} V_{min} \le V(t) \le V_{max} \\ Q_p(t-1) + V(t-1) - V(t) \ge Q_C(t-1), \forall t = 1, \dots, 24 \\ 0 \le Q_p(t) \le Q_{max} \end{cases} \quad (19)$$

Where: P_p is the power of pump n, and $u(t, n) \in [0, 1]$ is the operating state of pump n at time t (binary or continuous if variable-speed).

$$P_i(t,n) = \frac{\rho.g.H(t,n).Q_p(t,n)}{\eta(t,i)} \quad (20)$$

With :

t_f: pumping time (24 h);

n_p : number of pumps;

ρ : density of water (kg/m^3);

g : acceleration due to gravity (m/s^2);

$H(t, n)$: pumping pressure at time t with n pumps operating (m);

Q_p : pumping flow rate at time t with n pumps operating (m^3/s), expressed by:

$$Q_p(t) = \sum_{n=1}^{n_p} Q_n(t,n).u(t,n) \quad (21)$$

Where:

η : pumping efficiency at time t with n pumps operating (%)

V_{min} and V_{max} : minimum and maximum volumes in the reservoir, respectively (m^3);

$V(t)$: volume of water in the reservoir at time t (m^3);

$V(t-1)$: volume in the reservoir at time t-1 (m^3);

$Q_p(t-1)$: pumping flow rate at time t-1 (m^3);

$Q_c(t-1)$: consumption flow rate at time t-1 (m^3/s);

Q_{max} : maximum pumping flow rate (m^3/s).

To handle constraint violations, a penalty function is added to the objective:

$$f'(x) = f(x) + \lambda \cdot \left[\sum_{t=1}^{24} max(0, Q_c - \sum_{n=1}^{3} Q_n(t,n).u(t,n)) + \sum_{t=1}^{24} max\left(0, V_{min} - V(t)\right) + max(0, V(t) - V_{max})\right] \quad (21)$$

where λ is a large penalty coefficient.

Through iterative application of selection, crossover, and mutation, the GA evolves the population until the stopping criterion is met. The resulting optimal schedule minimizes daily pumping energy while ensuring both demand coverage and reservoir operational safety.

4. Simulation Results and Discussion

4.1. Water Demand Forecasting Performance

The developed ANN model was trained and tested using historical data structured by month, day of the week, hour of the day, and the previous hour's consumption. The results indicate that the ANN effectively captured the nonlinear seasonal and daily variations in water demand. The Mean Squared Error (MSE) obtained during testing was 0 m^3, confirming the reliability of the forecasting tool. As illustrated in Fig.3, the predicted consumption closely follows the actual demand profile, with only slight deviations during peak hours, which are inherently more difficult to forecast due to sudden consumption fluctuations. Overall, the ANN model provides accurate short-term demand forecasting, which is crucial for efficient pump scheduling.

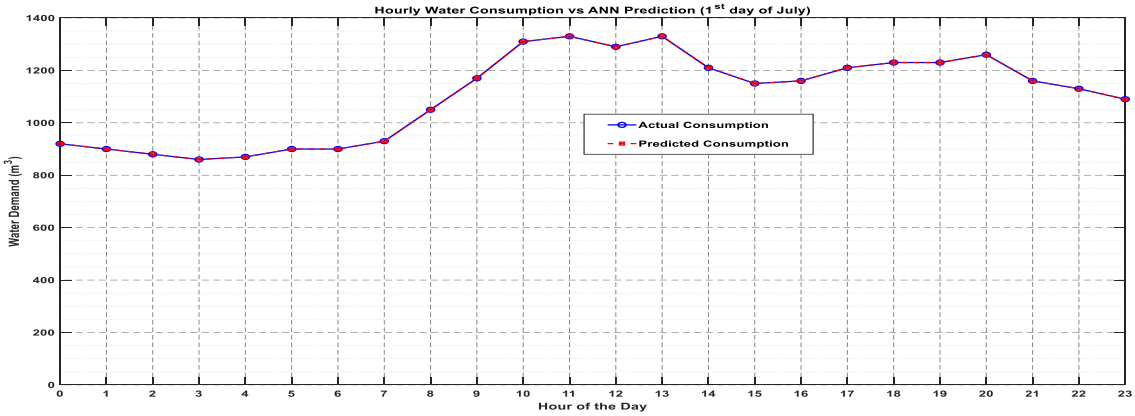


Figure 3. Daily water Consumption vs ANN Prediction

The Artificial Neural Network (ANN) was trained to forecast hourly water demand over one day. The training process converged rapidly, with the performance (Mean Squared Error, MSE) (Table 1) decreasing from 3.15 at epoch 0 to 1.54×10^{-21} at epoch 139, well below the target value of 0 and a Mean Squared Error: 0.00 m^3. This extremely low MSE demonstrates the ANN's strong ability to learn the underlying consumption patterns with high accuracy.

Table 1. Performances of the training process

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	139	1000
Elapsed Time	-	00:00:01	-
Performance	3.15	$1.54x10^{-21}$	0
Gradient	6.1	$4.99 x10^{-11}$	10^{-7}
Mu	0.001	10^{-9}	10^{10}
Validation Checks	0	0	6

4.2. Seasonal Variation of Water Consumption

In this case, the Artificial Neural Network (ANN) was trained to forecast hourly water demand over one year, considering seasonal variations, daily profiles, and short-term dependencies. Figure 4 compares the actual and predicted hourly water consumption for a typical day of each month. It can be observed that the predicted curves closely follow the actual profiles, capturing both the daily peaks (morning and evening) and the off-peak hours. The seasonal effects are also well represented:

- Summer months (June–August): The maximum consumption occurs due to high temperatures and increased water use, with peak hourly demand exceeding 1300 m³/h.
- Spring and Autumn: Medium consumption levels are observed, ranging between 900–1150m³/h, reflecting moderate climatic and domestic needs.
- Winter months (December–February): The lowest demand is observed, with consumption rarely exceeding 1100 m³/h.

These results validate the importance of considering seasonal variability in water demand management.

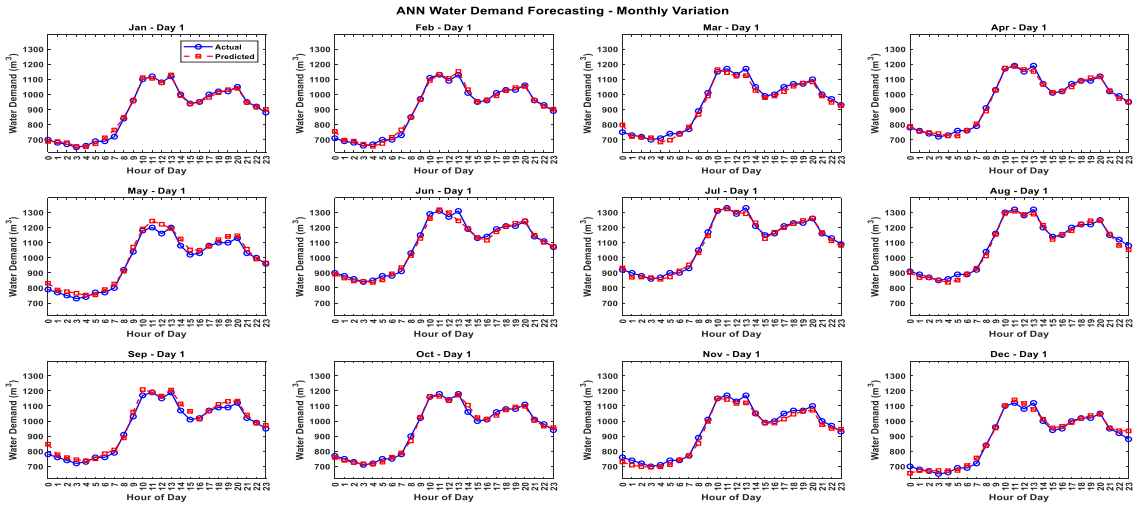


Figure 4. Monthly water Consumption vs ANN Prediction

4.3. Pump Operation Strategy

The pumping station is equipped with three centrifugal pumps, which operate either in classic or optimized strategy (Genetic Algorithm).

4.3.1. Classical pumping management

In classical strategy, pump 1 and pump 2 operate continuously at 100% capacity, regardless of actual demand, but Pump 3 is switched ON only when demand exceeds the combined flow of pump 1 and pump 2.

The reservoir level often reaches its upper limit because pumps deliver more water than required during low-demand periods. This leads to high energy consumption, as pumps are not adjusted to match variations in demand.

Figure 5 shows the classical pumps operation during each month. The simulation of pump scheduling showed the following:

- During low-demand hours (night and early morning), only one pump is sufficient to meet the required consumption.
- During medium-demand hours, two pumps operate simultaneously during peak hours (typically between 6-9 a.m. and 6-10 p.m.), ensuring sufficient water supply to match high demand.
- During peak hours (summer evenings), the third pump is activated to ensure sufficient water supply, avoiding reservoir depletion.

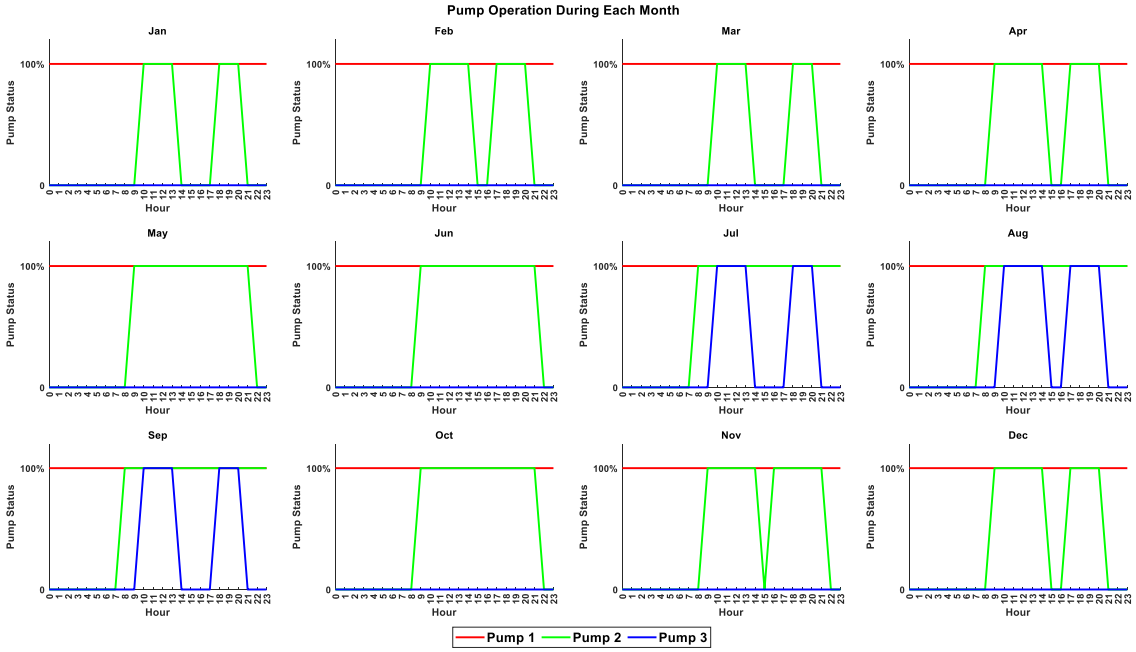


Figure 5. Classical management during each month

This result demonstrate that the classical management of pumping stations is rigid and energy-inefficient, leading to over- or under-pumping throughout the year due to its inability to adapt to seasonal and daily water demand variations.

4.3.2. GA-Optimized pump operation

In the optimized strategy, pump 1 and pump 2 no longer run constantly at 100%; instead, they operate at variable loads (0 –100%) depending on the demand and reservoir level. Pump 3 is activated only, when necessary, sometimes at partial load, to cover any remaining deficit in supply. The reservoir level is better balanced, maintained between safe limits without frequent saturation.

This results in significant energy savings, since the GA schedules pump usage more efficiently while still meeting all demand requirements. Figure 6 presents the optimized pumps operation during each month.

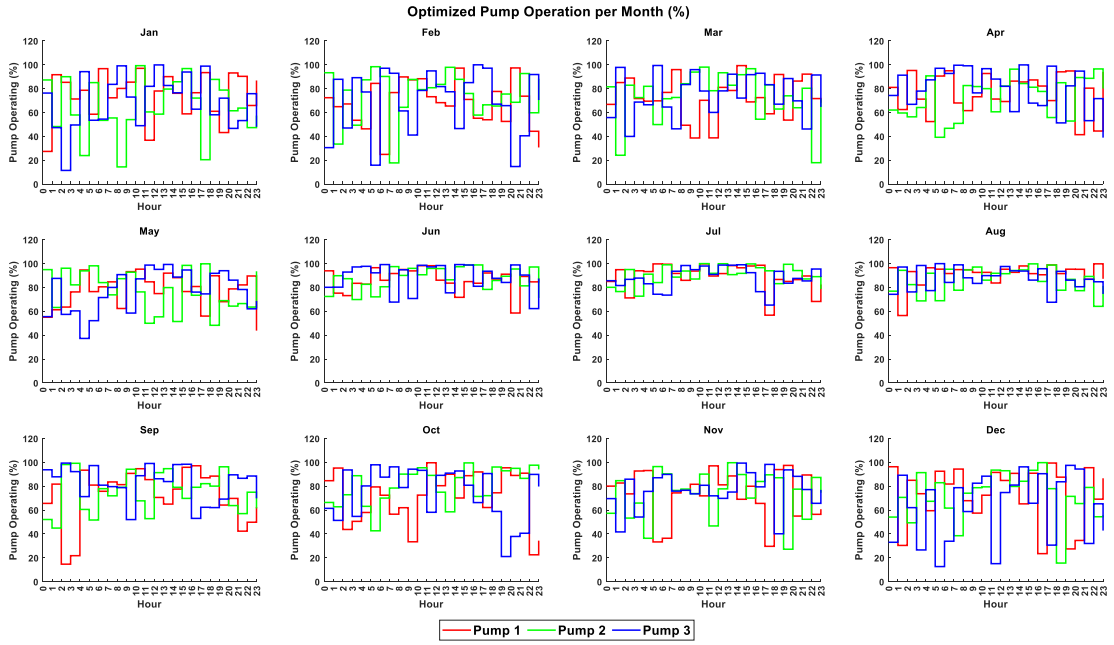


Figure 6. Optimized pump operation during each month

From this result we can see that:

- The GA-optimized strategy adapts pump operation to actual demand and reservoir conditions, avoiding unnecessary operation at full capacity. Compared to the classical approach, it reduces energy consumption while ensuring reliable water supply.
- All three pumps operate at variable loads (0–100%) throughout the day, dynamically adjusting to match hourly water demand.
- At Low-Demand hours, typically during night and early morning (0–6 a.m.), at least one pump operates at partial load, while the others are reduced or off, minimizing energy consumption.
- In Medium-Demand Hours, in the morning (around 6–9 a.m.) and evening (around 6–10 p.m.), two pumps operate, sometimes at full capacity and sometimes partially, to meet moderate increases in consumption.
- During Peak-Demand Hours, during high-demand periods (usually late afternoon/evening in summer months), the third pump is activated as needed, sometimes partially, ensuring sufficient water supply and avoiding reservoir depletion.
- For Seasonal Variation, demand peaks and pump load patterns vary slightly by month, reflecting seasonal consumption changes. For example, summer months show more frequent engagement of the third pump compared to winter months.

This optimized load-shedding strategy ensures a reliable water supply to the western part of Gabes, while minimizing unnecessary energy consumption. The forecasting tool thus provides a valuable basis for real-time pump scheduling, enabling SONEDE to enhance operational efficiency and energy savings.

4.4. Energy Optimization and Savings

Figure 7 shows the comparison between the daily energy consumed by the 3 pumps in conventional mode and in optimized mode (GA) with Anfis Neural Network prediction (ANN) of water consumption.

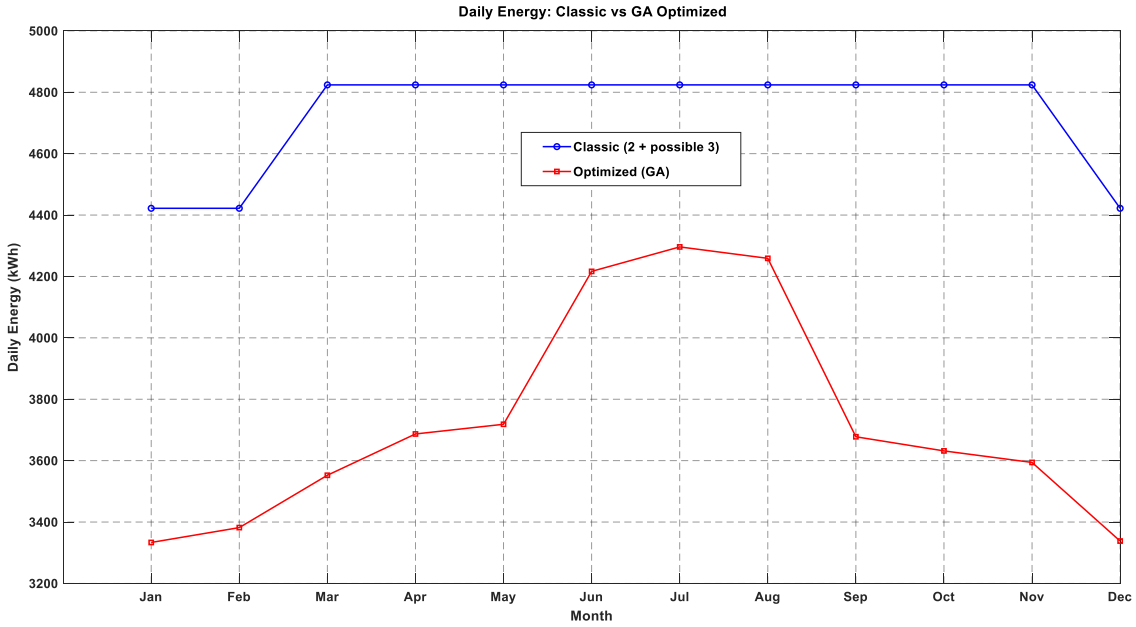


Figure 7. Daily Energy, Classic vs GA optimized

This result evaluates the impact of energy optimization on the energy consumption of three pumps. When operating at full capacity, the theoretical daily energy consumption of the pumps is 4,824 kWh. After optimization, the average daily consumption is reduced to 3,723.86 kWh, resulting in an annual consumption of 44,686.36 kWh. This optimization achieves annual energy savings of 13,201.64 kWh, representing a 22.81% reduction compared to the theoretical maximum consumption. These results demonstrate the effectiveness of optimization strategies in reducing energy demand while improving operational efficiency.

The integration of ANN-based demand forecasting with pump scheduling optimization using genetic algorithms demonstrated significant energy savings.

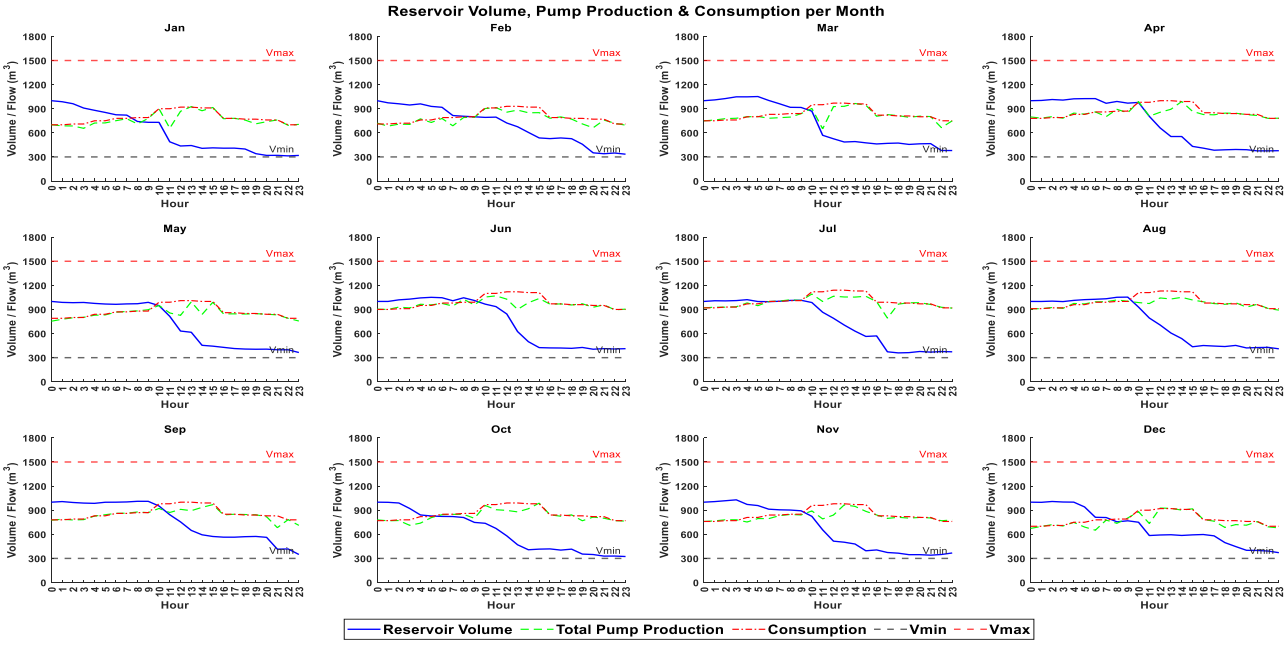


Figure 8. Impact of energy optimization on the energy consumption of three pumps

The results obtained highlight that the proposed management tool is effective in addressing both forecasting and optimization challenges in water pumping management. ANN forecasting provides accurate, real-time

consumption predictions and Genetic algorithm optimization ensures efficient scheduling of pumps, balancing demand satisfaction, reservoir constraints, and energy savings.

5. Conclusion

Sustainable water management is increasingly critical in the face of growing urban demand and rising energy costs. Water pumping stations, as key components of distribution networks, are among the largest consumers of electrical energy in municipal systems. Inefficient operation not only leads to excessive energy use but can also result in water losses and increased operational costs. This underscores the urgent need for intelligent management systems that optimize both energy and water use.

The proposed management tool demonstrates how Artificial Neural Networks (ANN) for water demand forecasting, combined with Genetic Algorithms (GA) for pump scheduling optimization, can transform the operation of pumping stations. By accurately predicting demand and optimizing pump operations within hydraulic constraints, RNAG ensures efficient water delivery while significantly reducing energy consumption. Simulation results show energy savings of up to 39.4% in a single day, reflecting both economic and environmental benefits.

Intelligent pumping management systems like the proposed tools are essential for modern water utilities. They enhance resource efficiency, reduce operational costs, and contribute to broader sustainability goals by conserving both water and energy. Future developments should focus on real-time adaptive control, multi-station coordination, and integration with renewable energy sources, further strengthening the resilience, efficiency, and environmental performance of water distribution networks.

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