Gated Recurrent Unit for Load Forecasting of Water Pumping Stations in Jebel Akhdar

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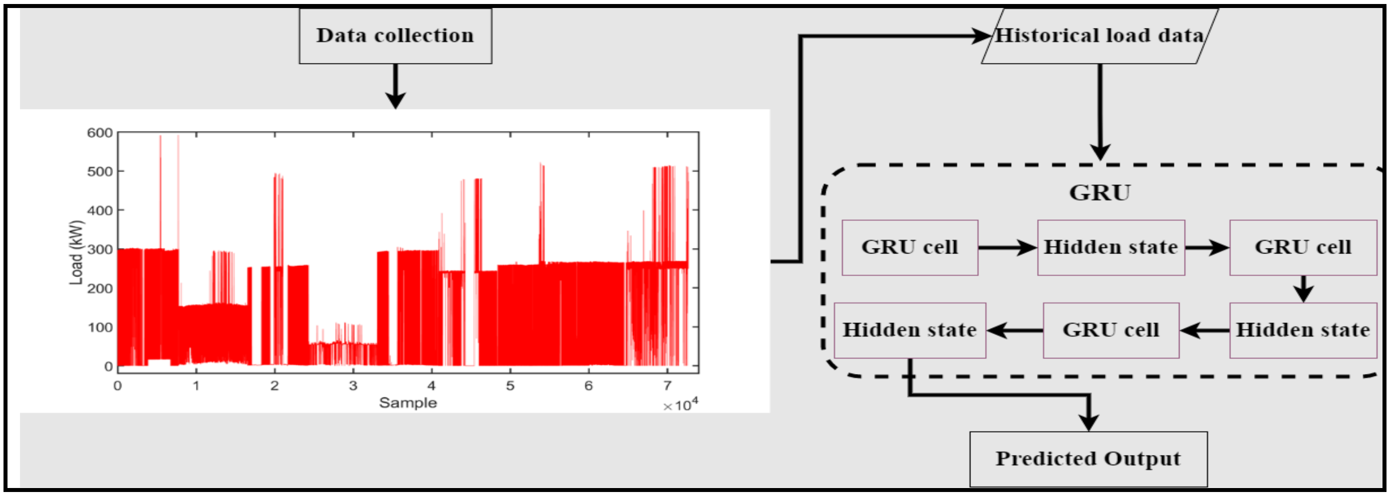

ABSTRACT: The relationship between water demand and electrical power consumption is critical as water transmission systems necessitate considerable amounts of energy. Accurate load forecasting for water pumping stations can improve the proper administration of energy, reduce inefficiency, and improve profitability. The application of contemporary deep learning techniques can significantly optimize energy consumption, save expenditures, and promote sustainable development in the context of water pumping stations. Moreover, precise load forecasting is essential for the proper functioning and energy management of water pumping stations, especially in areas with intricate topographical circumstances. Hence, this research utilizes Gated Recurrent Units (GRUs) to forecast the load demands of water pumping stations in Jebel Akhdar. The suggested model is specifically intended to capture the temporal dependencies and non-linear patterns that are inherent in the load demand data of the water pumping stations. In this regard, GRUs excel in their ability to dynamically update the hidden state, allowing them to capture complex temporal patterns accurately. Therefore, this study offers specific insights and solutions that may be used to comparable places characterized by intricate time-series variables. The approach provides superior prediction accuracy compared to standard forecasting methods by using historical load data. The findings of this work illustrate valuable insights for utility regulators to optimize energy usage and ensure sustainable water delivery.

Keywords: GRU; Jebel Akhdar; Load Forecasting; Water Pumping Station

وحدة الذاكرة التكرارية ذات البوابة (GRU) لتنبؤ الأحمال في محطات ضخ المياه في الجبل الأخضر

رزاق الاحسان*، محمد شدمان عابد، محمد العبري

الملخص: تعتبر العلاقة بين الطلب على المياه واستهلاك الطاقة الكهربائية أمر بالغ الأهمية لأن أنظمة نقل المياه تتطلب كميات كبيرة من الطاقة. يمكن للتنبؤ العميق الحديث أن يحسن الإدارة السليمة للطاقة في محطات ضخ المياه، ويقلل الفاقد، ويعزز الكفاءة الاقتصادية. كما أن تطبيقه يوفر تكلفة رأس المال وتكلفة التشغيل، ويعزز التنمية المستدامة لمحطات الضخ. علاوة على ذلك، يعد التنبؤ الدقيق بالأحمال أمرًا ضروريًا للتشغيل السليم وإدارة الطاقة لمحطات ضخ المياه خاصة في المناطق ذات الظروف الطبوغرافية المعقدة. ركزت هذه الدراسة على استخدام وحدات التكرار المغلق (GRUs) للتنبؤ باحتياجات الأحمال لمحطات ضخ المياه في منطقة الجبل الأخضر، حيث تم تصميم النموذج المقترح خصيصًا لاستيعاب الأنماط الزمنية المعقدة وغير الخطية التي تُميز بيانات الطلب على الأحمال. تُظهر وحدات التكرار المغلق قدرة متميزة على تحديث الحالة الداخلية ديناميكيًا، مما يُمكّنها من التنبؤ بدقة عالية بالأحمال الزمنية. تُبرز نتائج هذه الدراسة فعالية النموذج في تحقيق دقة تنبؤ أعلى مقارنة بالأساليب التقليدية من خلال تحليل البيانات التاريخية للأحمال. وتوفر هذه النتائج رؤى قيمة تساعد الجهات المعنية في تحسين كفاءة استهلاك الطاقة وضمان توفير مياه مستدام، خاصة في المناطق ذات الظروف الجغرافية المعقدة.

الكلمات المفتاحية: وحدة الذاكرة التكرارية المحكومة; الجبل الأخضر; التنبؤ بالأحمال; محطة ضخ المياه

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1. INTRODUCTION

The need for clean energy and water is experiencing a substantial increase as a result of the rapid development of the global population, industrialization, and evolving patterns of power and water use (Xu & Yang, 2024). From 2011 to 2030, the worldwide energy demand is projected to grow at an annual rate of 1.6%, resulting in a 36% rise in global energy consumption (Abid, Ahshan, Abri, Al-Badi, & Albadi, 2024). The present global water consumption is 4.6 trillion cubic meters per year. It is projected to rise by 20-30% by 2050, reaching 5.5-6.0 trillion cubic meters per year. Water supply systems, including pumping, treatment, and distribution, need significant energy (Wang, Xie, Liu, Yu, & Wang, 2024). On a global scale, the water industry contributes significantly to the total energy consumption. For example, in certain geographic regions, the usage of energy connected to water accounts for as much as 8% of the overall energy consumption (Tang, et al., 2024). The use of electricity in water networks is a crucial element of their functioning, including numerous operations such as water extraction, purification, and distribution. Pumps, the primary energy consumers in these systems, transport water from sources such as rivers, lakes, or underground aquifers to treatment facilities, and then to end-users. Furthermore, the process of operating the water distribution networks in order to transport water to residential, commercial, and industrial consumers necessitates substantial energy consumption. Thus, effective energy management and accurate load forecasting in these networks are essential for minimizing operating expenses, improving sustainability, and guaranteeing dependable water supply services.

Oman’s water supply system mainly depends on desalination, which is a significant user of electrical power. Oman has made substantial investments in desalination technology in order to fulfil its increasing water requirements (Rupiper, Good, Miller, & Loge, 2024). Desalination facilities are among the most significant power users in the nation. Water pumping stations, particularly in geographically difficult areas such as Jebel Akhdar, need a substantial amount of electrical energy to guarantee sufficient water supply (Al-Busaidi, Janke, Menezes-Blackburn, & Khan, 2022). In the Sultanate, the average cost of producing water is 0.455 OMR per cubic meter, while the cost of distributing water in Jabel Akhdar is 0.972 OMR per cubic meter (Oman Water and Wastewater Services Company, 2024). The cost of distributing water in Jabel Akhdar is more than double the cost of production. The significant costs are primarily a result of the use of energy-intensive pumping stations that provide the necessary flow rate and pressure in the water distribution network (Grobe, Urai, Littke, & Lünsdorf, 2016). For instance, the water present in Birkat Al Mouz necessitates the use of five pumping stations to elevate the water for customers located at the summit of Jabel Akhdar. It is important to note that the distance from Birkat Al Mouz to the summit of the mountain is about 34 kilometres, requiring the use of five pumping stations. Therefore, the correlation between water demand and electrical power use is crucial in Jabel Akhdar. Oman's energy strategy prioritizes enhancing water and energy use and the government is now investigating alternative energy sources to fuel water infrastructure, intending to decrease the amount of carbon emissions and improve long-term viability (Tse, 2024). Therefore, utilizing modern approaches, efficient load forecasting and control of the water pumping stations of Jabel Akhdar may substantially impact optimizing energy consumption, minimizing expenses, and fostering sustainable growth (Kow, et al., 2024). Precise load prediction for water pumping stations in Jebel Akhdar can also enhance the use of electrical power, minimizing inefficiency and enhancing effectiveness. Moreover, accurate load forecasting in Jabel Akhdar may facilitate the incorporation of renewable energy sources, such as solar or wind, into the energy combination by maximizing their use and decreasing dependence on costlier, non-renewable energy sources.

In water networks, energy losses can occur due to various factors, such as pump inefficiencies, leaks, and distribution losses. These losses highlight the need for an effective energy management strategy, where accurate load forecasting plays a critical role in optimizing operational efficiency and reducing overall energy consumption. Previous studies used several computational techniques to handle water pumping stations and associated difficulties effectively. Researchers in (Shao, Zhou, Yu, Zhang, & Chu, 2024) suggest an innovative approach to linearize the nonlinear problem by providing an optimization-based technique to dynamically modify the number of breakpoints used in the piecewise linearization process. The technique achieved competitive computational efficiency and energy cost savings by minimizing the number of auxiliary variables. The study in (Brentan, Mota, Menapace, Zanfei, & Meirelles, 2024) thoroughly examines the most effective functioning of pumps, taking into account both energy efficiency and water quality as the main goals. The model is gradually modified by adding a series of limitations to assess how they affect the ultimate operating plan. At first, the Particle Swarm Optimization (PSO) technique is used for single-objective optimization, which is a reliable and often used method in water resources research. The research conducted in (Shahhosseini, Najarchi, Najafizadeh, & Hezaveh, 2023) specifically examined the intricate configuration of the water distribution network (WDN) in the north-west region of Tehran. This network consists of 1124 pipes with a total length of 92552 meters, as well as four gravity reservoirs and 988 nodes. The optimization approaches of Genetic Algorithm (GA) and Nonlinear Programming (NLP) were used to improve the Water Distribution

Network (WDN) by reducing leakage and enhancing its resilience. Moreover, different computational techniques, such as heuristic algorithms, statistical models, and traditional machine learning methods, have been applied to manage water pumping stations. However, the comparison shows that optimization-based models and hybrid approaches often outperform others in terms of efficiency and accuracy, highlighting the importance of choosing the right method for effective water management (Al-Busaidi, Janke, Menezes-Blackburn, & Khan, 2022) (Shahhosseini, Najarchi, Najafizadeh, & Hezaveh, 2023). Moreover, various machine learning algorithms were used in recent research for electricity load forecasting applications. Authors in (Giberti, Dereli, Bahramian, Flynn, & Casey, 2024) conducted load forecasting using a high-frequency reference dataset derived from the Urban Water System model. More specifically, the researchers examined the performance of autoregressive models with time-delay networks, nonlinear autoregressive networks, and long short-term memory networks. A new spatiotemporal graph attention-enabled Transformer was introduced in (Zhao, et al., 2024) for the purpose of multivariate residential load forecasting. Unlike standard Transformer-based models, this model takes into account spatial correlations across numerous homes. (Zhang, Zhou, Xu, & Li, 2024) introduced a multivariate Transformer-based model designed specifically for direct net load forecasting. This design aims to enhance the extraction of multi-scale characteristics and capture the relationships between the net load and the relevant parameters. The authors in (Dong, Tian, & Lv, 2024) suggested an updated optimization method called IGWO-JAYA, which improves upon the Grey Wolf Optimizer (GWO) algorithm by including the use of the Halton low-discrepancy sequence and the mechanism of the JAYA algorithm. The suggested optimizer was used in data elimination to improve the Variational Mode Decomposition (VMD), which allows for adaptive noise reduction based on data analysis. In the study conducted in (Song, et al., 2024), the challenge of predicting multi-energy loads is converted into a hierarchical multi-task learning problem. This is accomplished through the use of a stochastic focus mechanism and a controlled longitudinal convolutional model. In order to enhance the effectiveness of short-term power load forecasting, a load forecasting approach is designed in (Wang, Chen, Xiao, Yang, & Yao, 2024) that incorporates user behaviour through an empirical mode decomposition algorithm. Lately, deep learning models, specifically models constructed using GRU, have been extensively used in present research for time-series forecasting. For example, researchers in (Chiu, Hsu, Chen, & Wen, 2023) have shown that Convolutional Neural Networks (CNNs) are capable of extracting valuable information from power load data with high levels of uncertainty. Additionally, they have found that GRUs provide advantages in time-series forecasting. In (Li, et al., 2022), researchers provide a new framework that combines the Bidirectional GRU and Sparrow Search Algorithm to enhance the precision of oil rate forecasts. In (Xu, et al., 2024), the authors offer a novel approach that combines GPU and XGBoost models to enhance the accuracy of prospective renewable energy hourly predictions. The suggested methodology encompasses numerous phases, including data preparation, constructing features, development of GRU and XGBoost mathematical models, and the amalgamation of the forecast outputs. In (Liu, Shi, Sun, Lin, & Li, 2024), a net load hybrid forecasting model named CNN-GRU is introduced. The results of the forecasting demonstrate that the suggested model is capable of successfully handling weather fluctuations while retaining a high level of predictive accuracy.

1.1 Problem Statement

Water pumping stations are essential infrastructure for guaranteeing a dependable water supply, particularly in areas with difficult geographical and climatic circumstances such as Jebel Akhdar. Nevertheless, the effective functioning of these stations for efficient energy management relies significantly on precise load forecasting. Conventional load forecasting techniques often struggle to accurately account for the intricate time-based relationships and non-linear trends in load data, resulting in less than optimum energy management and higher operating expenses. Insufficiently accurate load estimates may lead to either excessive strain on resources or inadequate use, which can have a negative impact on the sustainability and dependability of water distribution. Hence, there is an urgent need for sophisticated forecasting methods that can provide more precise and dependable load estimates to improve the operational efficiency and energy management of water pumping stations in Jebel Akhdar. Current load forecasting techniques for water pumping stations mostly depend on linear models or basic approaches that do not adequately account for the intricate temporal relationships and non-linear patterns in the data. Furthermore, despite the progress made in deep learning, there is limited application of advanced models such as Gated Recurrent Units (GRUs) for load forecasting, specifically in the context of water pumping stations. Furthermore, more research needs to be done that explicitly addresses load forecasting for water pumping stations in geographically distinct areas like Jebel Akhdar, where local characteristics may have a substantial impact on load patterns.

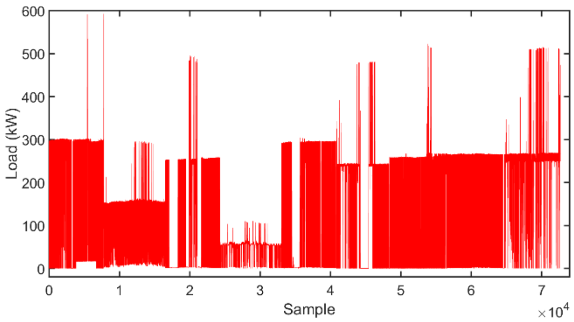

Figure. 1. Load data in time-series representation

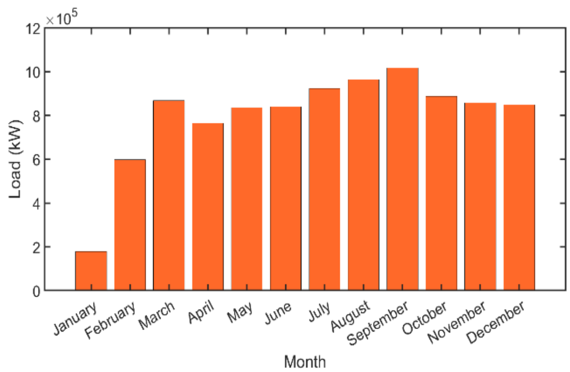

Figure. 2. Load data in time-series representation (Monthly distribution)

1.2 Research Objectives

This work presents the use of Gated Recurrent Units (GRUs) for load forecasting in water pumping stations, showcasing their capacity to effectively manage intricate temporal relationships and non-linear patterns in load data. The proposed model was compared to the conventional Multi-layer Perceptron (MLP) based model. The use of advanced models such as Gated Recurrent Units (GRU), specifically in the context of water pumping stations, significantly improves prediction accuracy in comparison to MLP, as shown by comprehensive performance measures. This study focuses on the distinct difficulties of load forecasting in Jebel Akhdar, offering customized insights and solutions that may be used to compare places characterized by intricate topographical and meteorological circumstances. The model utilizes a wide range of data inputs, such as historical load data and operating schedules, to enhance the strength and dependability of load projections. This study enhances energy management and operational efficiency of water pumping stations by providing more precise load projections, hence supporting sustainable water distribution practices.

2. METHODOLOGY

The gated recurrent unit (GRU) was initially developed to enable each recurrent unit to capture dependencies of varying time scales dynamically. Like the Long Short-Term Memory (LSTM) unit, the GRU also includes gate modules that control units with a reduced number of gates and parameters. This simplicity often results in accelerated training periods and simplified implementation. The update gate, denoted as z, determines the extent to which the unit modifies its activation. Firstly, the update gate is calculated by:

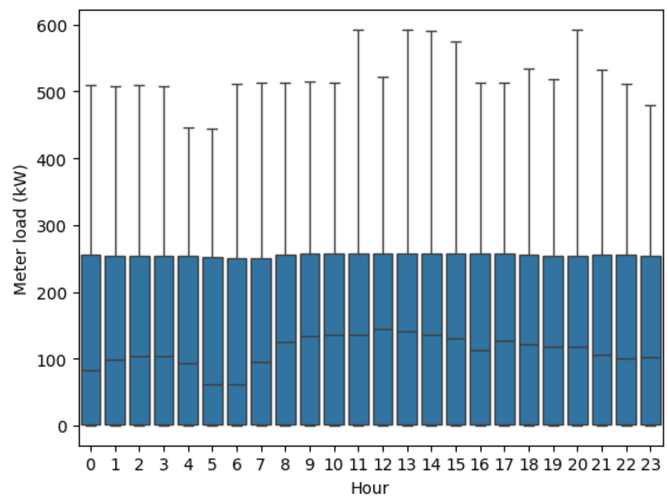

Figure 3. Load data in time-series representation (Hourly distribution) (Oman Water and Wastewater Services Company, 2024)

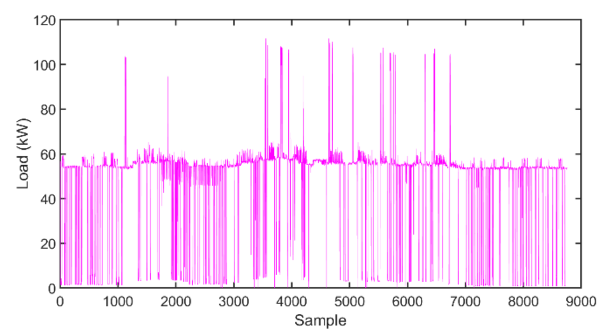

Figure 4. Load data of sample meter 1 (Oman Water and Wastewater Services Company, 2024)

$$z_t = \sigma\left(W_z \cdot x_t + U_z \cdot h_{(t-1)} + b_z\right) \quad (1)$$

where t represents the iteration, x is the input, U and W are weight matrices, b represents bias vectors, and h represents the hidden state. The process of calculating the linear combination of the current state and the newly calculated state is analogous to the LSTM unit. GRUs, with a reduced number of parameters, have a lower susceptibility to overfitting in comparison to more intricate models such as LSTMs. This advantage is especially evident when working with smaller datasets. The GRU lacks a mechanism to regulate the level of state exposure, resulting in the complete exposure of its whole state on each occasion. Hence, the candidate activation function is calculated in a manner that is comparable to the standard recurrent unit, such as:

$$\tilde{h}_t = tanh\left(W_h \cdot x_t + r_t \circ \left(U_h \cdot h_{(t-1)}\right) + b_h\right) \qquad (2)$$

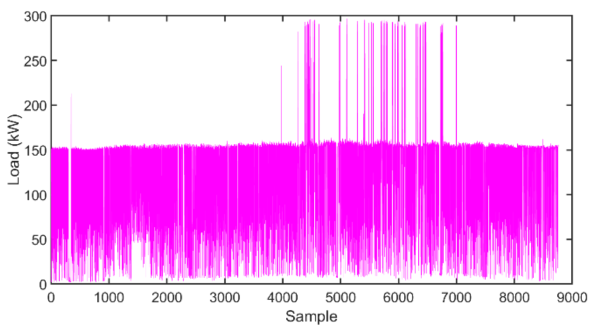

Figure 5. Load data of sample meter 2 (Oman Water and Wastewater Services Company, 2024)

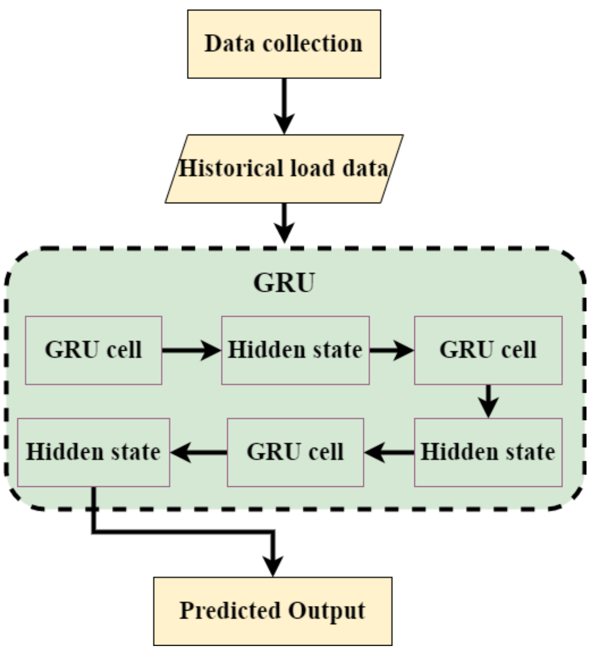

Figure 6. Implementation of GRU-based load forecasting

where r represents a collection of reset gates with the operation of element-wise multiplication. When the reset gate is turned off (near 0), the unit behaves as if it is receiving the first symbol of an input sequence. This allows it to disregard the previously calculated state.

Table 1. Results Analysis.

Algorithm	MLP	GRU
Test MSE	0.0090	0.0077
Training MSE	0.0078	0.0076
Batch size	16	16
Epoch	100	100
Optimizer	Adam	Adam
Dropout	-	0.2

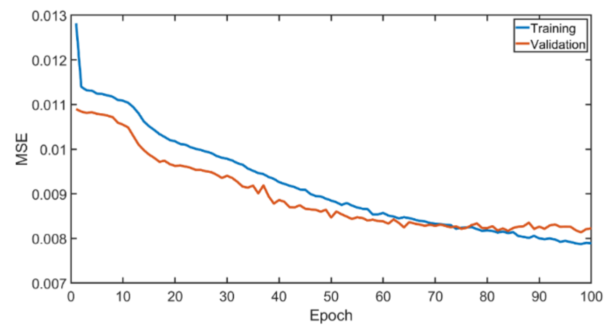

Figure 7. Train VS validation using GRU.

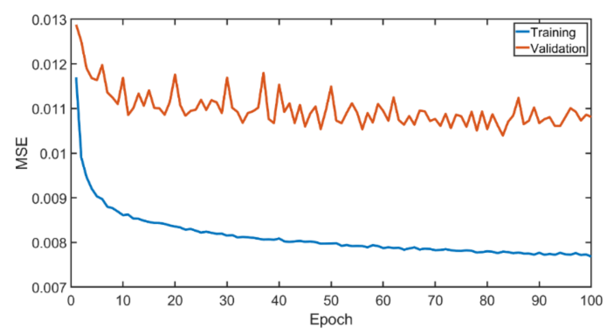

Figure 8. Train VS validation using MLP

Hence, the computation of the final hidden state (h) is performed using the following method:

$$h_t = z_t \circ h_{(t-1)} + (1 - z_t) \circ \tilde{h}_t \qquad (3)$$

Moreover, the computation of the reset gate r, is analogous to that of the update gate:

$$r_t = \sigma\left(W_r \cdot x_t + U_r \cdot h_{(t-1)} + b_r\right)$$
(4)

Therefore, the update order of the reset gate enables the decreased quantity of hyperparameters in GRUs

the hyperparameter tuning procedure, facilitating the optimization of the model for particular tasks. GRUs often use less computer resources and memory than LSTMs due to their more straightforward structure and fewer parameters. This characteristic makes them well-suited for use in situations where there are constraints on the available processing resources. The simplified structure of GRUs may result in accelerated training and inference durations, facilitating expedited development cycles and real-time implementations. Although GRUs have a less complex structure, they have been shown to achieve similar or superior performance compared to LSTMs in a range of sequential and time-series prediction tasks.

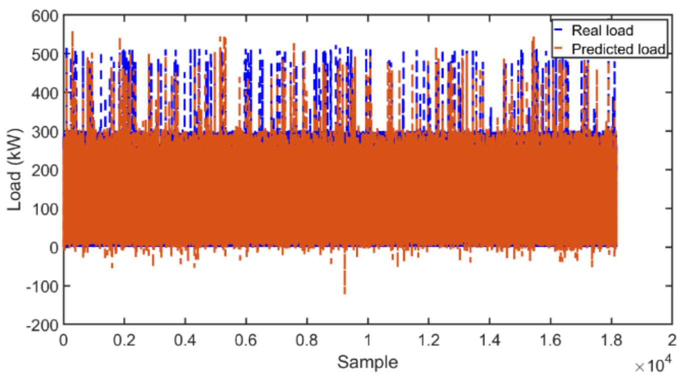

Figure 9. Prediction using GRU.

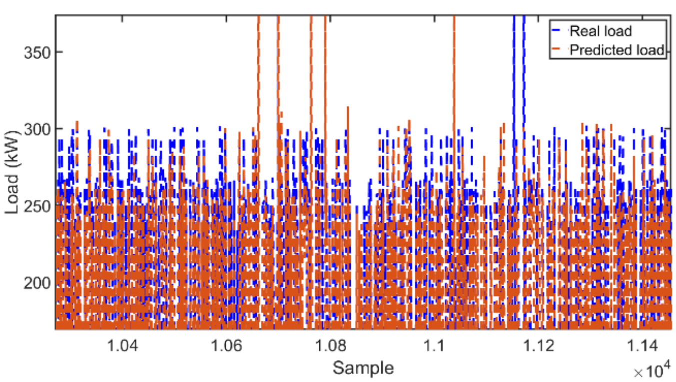

Figure 10. Prediction using GRU (zoomed version).

3. DATA ANALYSIS AND SIMULATION

This study utilizes the historical load data obtained from the Jebel Akhdar water pumping stations over a period of one year (Oman Water and Wastewater Services Company, 2024). Fig. 1 illustrates the whole dataset used for both training and testing purposes in this study. It is important to note that, all the loads are in kW units. Fig. 2 depicts the monthly distribution of the load data. August to November are the months with the greatest demand for power, with September being the peak month. Fig. 3 illustrates the hourly distribution of the load data. It is evident that the load values are greater throughout the mid-hours of the day, particularly between the 10th and 14th hour, with the peak generally occurring around the 13th hour. Furthermore, Fig. 4 and Fig. 5 illustrate the yearly (8760 hours) sample meter load data from the pumping stations. It has been observed that load data tends to peak during the middle months of the year, especially from July to September. It is important to note that, during the simulation, all the meter data were added with respect to the respective hours of the yearly data. Moreover, in terms of the simulation, the GRU neural network is structured using an architecture that has input, hidden, and output layers. GRUs are selected for their capacity to grasp temporal relationships in sequential data using a more streamlined design and achieving quicker convergence in comparison to LSTMs. The most relevant characteristics are mainly chosen from the processed data for training purposes. This entails determining the most influential factors that impact the load.

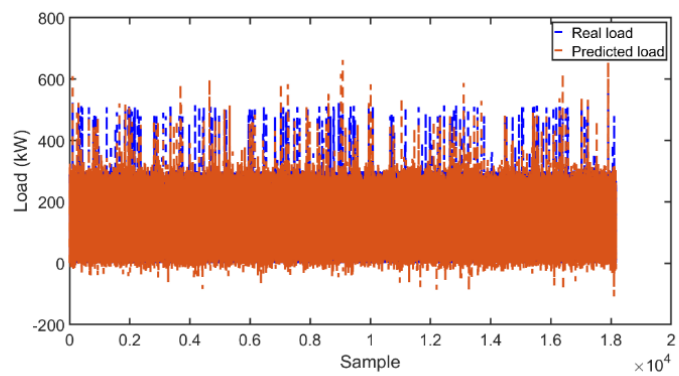

Figure 11. Prediction using MLP.

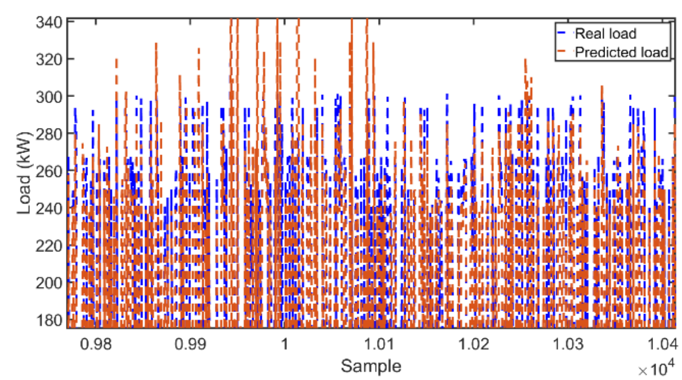

Figure 12. Prediction using MLP (zoomed version).

Patterns, including time of day, day of the week, and previous load levels. The training procedure passes the input data through the GRU layers, improving the network weights by backpropagation, and reducing the difference between anticipated and actual load levels. The verified model undergoes a process of fine-tuning hyperparameters and preventing overfitting by utilizing a distinct validation dataset. The suggested model's flowchart is depicted in Fig.6. Once the model has been validated, it is next assessed using a separate test dataset in order to evaluate its performance. Metrics like Mean Squared Error (MSE) are used to measure the precision of load projections.

4. RESULTS ANALYSIS

In this study, the performance of the suggested GRU model is compared to the Multi-Layer Perceptron (MLP) technique (Hontoria, Aguilera, & Zufiria, 2005). Forecasting curves and error metrics are used to demonstrate the model's superiority in certain load forecasting tasks for water pumping stations. Table 1 displays model results by batch size, epoch, optimizer, and dropout rate for each technique. Observations indicate that the GRU model outperformed the MLP model by 3% in terms of training MSE. Furthermore, in terms of the overall MSE, the GRU yielded results that were 16% superior to those of the MLP. It is evident that GRU yields greater outcomes in terms of prediction. Furthermore, Fig. 7 depicts the training and validation curves for the GRU model. Empirical evidence demonstrates that the training and validation curves exhibit a high degree of consistency by achieving a rapid and reliable convergence. This demonstrates the efficacy of GRU in terms of minimizing loss and accurately predicting the projected outcomes. The optimal validation accuracy in GRUs is perceived due to their specialized architecture for handling sequential input and capturing long-term relationships. GRUs provide enhanced robustness in extrapolating to unfamiliar data owing to their capacity to preserve and manipulate information over extended sequences, hence mitigating the risk of overfitting. The design of GRUs naturally serves as a method of regularization by preserving pertinent information over time, hence mitigating the risk of overfitting. GRUs excel at managing temporal dependencies and sequential patterns, resulting in superior adaptation to validation data. On the other hand, Fig. 8 displays the train and validation curves for the MLP model. It has been noted that although the MLP model's training performance demonstrates early convergence, the validation curve exhibits irregular patterns in terms of prediction.

The validation accuracy decreases in the MLP model due to the challenges faced by the feedforward neural network design in capturing temporal relationships in sequential input. MLP is particularly susceptible to overfitting, particularly when the dataset is insufficient in size or when the network is too deep. The model has achieved high performance on the training data, even when faced with noise and certain patterns that do not apply to fresh data. Nevertheless, MLPs that include several layers and neurons have a significant capability to recall the training data, resulting in a low training error but an elevated validation error.

Moreover, Fig. 9 illustrates the comparison between the actual and anticipated values for all the samples using the suggested method. The GRU model's predictions (red dots) closely correspond with the true data (blue dots), as per the zoomed version depicted in Fig. 10. The findings shown in Fig. 10 illustrate that the GRU model has effectively identified the temporal correlations of the water system electrical load data and produced improved outcomes. GRUs have superior predictive capabilities because of their specialized architecture for sequential data processing. GRUs possess latent states that gather information from preceding time steps, making them proficient in acquiring temporal dependencies. Moreover, GRUs possess gating mechanisms, namely update and reset gates, which aid in preserving long-term dependencies and eliminating extraneous input.

Furthermore, GRUs have the ability to catch extended-term trends and recurring patterns that are inherent in load data, resulting in more precise predictions. Nevertheless, the outcomes shown in Fig. 10 exhibit a much higher level of excellence as they demonstrate a closer alignment, hence substantiating the fact that GRU has surpassed MLP in terms of forecasting performance.

GRUs benefit from their capacity to dynamically update the hidden state, enabling them to effectively represent intricate temporal patterns. Moreover, GRUs have the ability to acquire representations straight from unprocessed sequential data without the need for complex feature engineering. This simplifies the process of modelling and has the potential to enhance forecasting accuracy Furthermore, Fig. 11 presents a comparison between the real and predicted values for all the samples using the recommended approach, with a closer view shown in Fig. 12. GRUs outperform MLPs in terms of predicting accuracy because MLP feedforward neural networks handle inputs in an environment that disregards the sequential nature of the data. This reduces their effectiveness in recording temporal dependencies. In order to process sequential data, MLPs need thorough feature engineering, including the creation of lag features. However, this process may be intricate and may not entirely capture the fundamental patterns present in the data. In addition, MLPs have the constraint of requiring input vectors of a set length. This might be a barrier when working with sequences of varying lengths in load forecasting. Furthermore, Figures 9 and 11 demonstrate that both models projected some negative values. This is because a significant number of the load levels were close to zero, which we identify as a research needs to be addressed in the future.

5. CONCLUSION

This study presents a novel approach that uses GRUs to predict the load requirements of water pumping stations in Jebel Akhdar. The proposed model is designed to explicitly capture the time-series relationships and complex patterns that naturally exist in large-scale load datasets. This research specifically examines the unique difficulties of load forecasting at Jebel Akhdar. Results show that considering the overall MSE, the GRU produced outcomes that were 16% better than those of the MLP. Furthermore, empirical data shows that the training and validation curves display a stable curve with early and consistent convergence. In addition, the predictions of the GRU model closely align with the actual data, demonstrating that the suggested model has successfully recognized the time-based relationships in the water load data and generated enhanced results. In conclusion, this work develops an efficient forecasting method to facilitate the operational efficiency of water pumping stations by offering accurate load estimates. Possible future contributions may include extending the GRU-based approach to incorporate additional factors, such as weather patterns to enhance the accuracy. Moreover, integrating attention mechanisms into the GRU model can improve the model's ability to identify inherent patterns within the load data.

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CONFILCT OF INTEREST

The authors affirm that they have no conflicts of interest with any organization in relation to this work.

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