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AI-Based Predictive Improvement of Energy Management Systems in UAE District Cooling Plant Using LSTM

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ABSTRACT:
Evaluate the performance of the Energy Management System in District Cooling Systems operated by a UAE-based company through predictive modeling using Long Short-Term Memory networks. While existing EMSs often lack adaptability to local conditions, this study proposes a predictive model that uniquely integrates UAE-specific environmental variables: such as ambient temperature, humidity, and wet bulb temperature, with real-time operational data like chilled water flow rates, supply/return temperatures, and energy consumption. Using historical and operational data from the company's DCS plants, the study develops LSTM-based models to forecast electricity consumption, cooling load, and system demand for 2025 with high temporal resolution. The developed deep learning model achieved excellent predictive performance, with coefficient of determination R^2 above 0.90 for all key metrics, Electricity (0.9569), Chilled Water (0.9878), and kW/TR efficiency ratio (0.9009), and prediction errors below 6%. The models are evaluated using statistical accuracy metrics (R^2, MAPE), and their integration into EMS will be tested through a pilot testing. This research is designed to improve chiller scheduling, reduce peak energy loads, and improve energy efficiency. The predictive model delivers measurable improvements in energy consumption and system improvements contributing to the company's sustainability goals and offering a scalable solution tailored to the UAE's operational environment.

KEYWORDS:
District Cooling Systems, Energy Management Systems, Artificial Intelligence, Machine Learning, Cooling Demand Forecasting, EMS Improvement, LSTM, XGBoost, and Energy Efficiency.

1) Introduction:

A critical component of the interior setting is thermal comfort. In addition to being crucial for human comfort, achieving ideal thermal comfort impacts the building's energy usage. Each resident adjusts the building's systems and parts to their preferred level of thermal comfort [24]. However, it is more challenging to provide cooling efficiently than heat because the need for cooling is more unpredictable than the heat demand, especially during peak periods. According to [1], cooling demand depends on several variables that can change rapidly, including sunlight, thermal gains, and the impact of urban heat islands. Furthermore, the electrical grid's stability is at risk due to the rising percentage of Renewable Energy Sources (RES) [3] Because RESs like solar and wind energy are intermittent, it is difficult to foresee and control them. As a result, maintaining a balance between power generation and consumption is becoming more complex, and there is a growing chance of blackouts and other technical problems. ring all of the above-mentioned factors, creating more effective cooling systems is essential to enhancing the sustainability of cities in the future.

Countries struggle to adjust to a changing environment as temperatures worldwide continue to increase. With their large infrastructures and dense populations, urban centers are at the forefront of this change. Residents of these urban areas have consequently turned to regulated indoor spaces for comfort, mostly depending on artificial cooling techniques [17]. An excellent illustration of this trend is Dubai, one of the most recognizable cities in the Middle East. Dubai experiences a hot summer that lasts from May to October. August is particularly harsh because temperatures regularly surge beyond 50 °C. Temperature rarely falls below 30 °C, even at night, ensuring artificial cooling is highly essential [12]; [5]. Residents of Dubai spend more than 90% of their time indoors due to the city's urban design and the unrelenting heat (Arar & Jung, 2021). However, growing dependence on air conditioning increase energy consumption.

At home, District Cooling System (DCS) is a possible solution to the increasing demand for cooling in Dubai [15]. Due to the energy efficiency of DCSs, these systems are often used to meet the increasing demand for refrigeration. The DCS is a centralized mechanism that generates and circulates cooling energy to provide cooling to several structures or areas. As a result of its innovative refrigeration technology and high energy management, this system can help save a good amount of energy step by step [26], thus making it more economical and environment friendly compared to traditional decentralized air-conditioning units. Reusing waste heat through various recovery technologies, such as converting it into electricity, using it to heat water, or storing it thermally (Thermal Energy Storage), reducing the need to build large generation plants, reducing transmission interruptions through on-site generation, increasing conversion rates, mitigating emission problems and the resulting financial gains, and utilizing RES are all made possible by DCS [16]. Therefore, utilizing a DCS is less expensive than exploiting a household cooling arrangement, and society is drawn to its low pollution levels. An essential factor in the increase in heat waves in the environment was the production and use of energy for residential and commercial uses. As a result, there is considerable concern regarding the high energy demand in buildings, given the increased use for comfort-driven purposes across the globe. Studies indicate that energy usage in these sectors has surged by 20–40% in developed regions, with residential and business buildings accounting for nearly 40% of total energy demand or 36% of Europe's carbon footprint [4]. In Asia, about 35% of building energy consumption is used for cooling and heating, while the UAE's residential sector alone constitutes 33% of the national energy use [4].In the UAE, District Cooling Systems (DCS) have been widely utilized to efficiently address large-scale cooling requirements. However, recent observations from various District Cooling Plants owned by A UAE-based company indicate that there are inefficiencies in energy management. These include suboptimal chiller scheduling, frequent reliance on static setpoints, and absence of real-time load predictions, which results in larger system operation and higher energy loss. Furthermore, centralized EMSs in some plants do not fully utilize real-time operational data or predictive analytics, resulting in avoidable peaks in electricity consumption and higher operational costs.

It has been estimated that cooling alone consumes 17% of global electricity and contributes approximately 8% of total greenhouse gas (GHG) emissions [4]. With rising temperatures and growing urban demand, DCS technologies especially those lacking adaptive EMS frameworks can significantly impact environmental sustainability. In the UAE-based company's DCP's, where chilled water system operates across diverse building types including residential and commercial units. inefficient control strategies can directly increase energy losses and carbon emissions to align with UAE Vision 2030 and the UAE Clean Energy Strategy 2050, which emphasize sustainable development, reduced greenhouse gas emissions, and increased energy efficiency across all sectors.

Therefore, there is a critical requirement to improve the performance of EMSs within the company's district cooling operations. This includes implementing predictive models for energy consumption and cooling demand, improving chiller scheduling efficiency, and integrating real-time monitoring tools. Increasing the energy efficiency of cooling systems is essential from both an economic and environmental perspective.

2) Literature Review

(a) Energy Management System in District Cooling System:

Energy Management System in District Cooling System: Effective cooling systems are becoming more and more necessary as cities grow and the world's thermostat increases. Energy management in DCSs becomes a crucial issue in this context, combining the concepts of cost-effectiveness, environmental stewardship, and operational efficiency [6]. EMS offers conventional practices to improve DCS energy efficiency, such as using high-efficiency chillers, improving insulation to reduce heat loss, and using variable frequency drives to adjust pump and fan speeds based on system demand. According to [6], EMS also provides sophisticated sensors and control systems for predictive maintenance procedures, which improves system responsiveness and dependability. Energy optimization expands upon the foundation laid by energy efficiency, which minimizes intrinsic energy waste by coordinating data-driven, intelligent system functionality administration. To enable an anticipatory approach to energy management, EMS enables DCS to use data analytics that offer operators insights into system activity [6]. Platforms for data analytics analyze the data, providing a perspective on system performance and pointing out areas for development.

EMS is crucial for improving DCS performance, and its effectiveness directly influences cost savings, operational reliability, and energy efficiency. Studies have highlighted various barriers and opportunities for improving EMS performance in district cooling systems. To optimize energy utilization and storage, [11] emphasized the importance of accurately estimating short-term cooling loads in building district energy systems (BDESs). High-precision demand prediction enables EMS to make real-time adjustments to operational parameters, ensuring efficient energy distribution and minimizing waste. The study also highlighted the significance of past cooling loads in forecasting future demands, underscoring the need to integrate real-time data into EMS for improved accuracy.

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To assess EMS in terms of productivity, economic factors, and environmental impact, [25] developed a comprehensive performance evaluation framework. This methodology prioritized performance indices using the Entropy Weight Method and Analytic Hierarchy Process (AHP), providing a well-rounded assessment of EMS. Additionally, the study demonstrated the substantial benefits of EMS optimization in complex systems, such as hospital buildings, where operational efficiency is critical, and energy consumption is high. [18] explored the integration of cooling demand flexibility into EMS. According to the study's empirical data, minor thermostat setpoint tweaks across several buildings can dramatically lower peak cooling demand, underscoring EMS's ability to integrate demand-side methods for improved performance. [25] presented a novel demand response administration grid-free DCS that uses blockchain technology and liquified natural gas (LNG) cold energy. Advanced energy recovery and separation from the power grid made this strategy an autonomous and sustainable EMS model. These studies highlight the importance of continuously evaluating and improving EMS performance, primarily through precise load forecasting, real-time data integration, and thorough performance evaluations.

The growth of EMS technology focuses on the integration of state-of-the-art hardware, optimization, and predictive models to increase system performance. [14] developed a real-time optimization system for district cooling systems that incorporates demand forecast, chiller optimization and cooling tower optimization to store every component operating effectively and cost-efficiently. In this work, the mixed-integer linear programming (MILP) technique was used to handle both discrete and continuous decision variables and optimize chiller operations for system-level optimization. Similarly, [25] reviewed various EMS enhancements, such as improving energy efficiency, fault detection, and optimizing chiller units. The efficiency framework in this study incorporated optimization methods like replacing faulty check valves and adjusting pump and fan frequencies, which led to significant energy savings. Two examples of performance metrics that support these improvements are the composite performance score and demand satisfaction rate.[25] presented a blockchain-native EMS architecture for the secure and decentralized implementation of demand response management. This approach enables decentralized governance and uses smart contracts to ensure real-time adaptability. Enhancing EMS capability requires the application of data-driven models and real-time optimization techniques, which give systems the capacity to react swiftly to shifting circumstances and boost operational effectiveness.

(b) District Cooling System in UAE: Compared to conventional cooling technologies, DCSs are substantially more efficient and use less energy. DCS are an alluring alternative because of the hot heat in much of the MENA region [20]. DCS has advanced significantly in the UAE, with several districts—specifically, Dubai—having already deployed their first intelligent DCSs networks. The station's electromechanical areas were decreased, and 30% to 50% less electricity was connected and used overall [20]. The world's leading urban cooling provider, Empower, established a test program for the initial remote-controlled chilling plant at Jumeirah Village Circle in 2020, marking a significant milestone for Dubai [23]. The cooling plant uses AI to track water flow to and from the facility [23]. During peak hours, thermal energy storage technology helps lower network demand.The establishment of DCS throughout the UAE has been made possible by leading suppliers like Tabreed, Empower, and Emicool. Tabreed has collaborated with Saudi Aramco on significant projects and runs DCS in multiple emirates. One of the biggest providers of district cooling services worldwide, Empower offers extensive district cooling services. In the United Arab Emirates, Emicool provides cooling solutions to the commercial, industrial, and residential sectors, substantially contributing to sustainable urban development.

DCS are known for using less energy and being more efficient than traditional cooling systems, which is why they are highly valued in the UAE for their superior energy performance. This makes them effective in lowering peak electricity demand and optimizing cooling loads, especially in the harsh climate of the United Arab Emirates [20]. Moreover, design and optimization enhancements are required in adapting according to region climate that maximize energy management and ensure that DC systems respond in an optimized manner during high seasonal demand periods [7].

The UAE plans to leverage DCS even more to advance the sort of sustainable and energy-efficient management. The UAE's future, such as the UAE Clean Energy Strategy 2050, reflect this expansion. Its goals include boosting energy efficiency and reducing greenhouse gas emissions while also unleashing economic growth. Integrating RES further increases the UAE's capacity for sustainable DCS [7]. Innovations to come will depend on breakthrough technologies, including AI-based optimization models and IoT-affixed sensors. Future innovations will be driven by cutting-edge technologies, including AI-based optimization models and IoT-enabled sensors. Moreover, the rapid urbanization in the UAE has increased the demand for energy-efficient and sustainable cooling systems. Well-planned DCS for new urban developments can significantly contribute to both sustainability and energy efficiency. According to [7], the UAE's goal of sustainable and equitable urban development will be supported by advanced modeling and management of DCS.

(c) Artificial Intelligence in District Cooling System: The emergence of increased data availability, data-driven models has raised some advanced control tactics. Thus, the technological improvement of AI brings new ideas for the challenges of carbon emission reduction and energy-saving of air conditioning systems [11]. By forecasting not only cooling demands but load management as well, AI can flexibly couple cooling demands and variable RES for an optimal energy system. Data-driven strategies that employ AI techniques like deep learning also add up to substantial energy savings. Including AI techniques will ensure that it can recognize when a building is unoccupied and adjust the temperature settings, such as raising the temperature in the summer or lowering it in winter.

(d) Role of Artificial Intelligence and Machine Learning in Energy Optimization: These systems, using sensors, data analytics, and AI, can drastically reduce energy waste and boost efficiency. By leveraging advanced analytics to track energy consumption patterns, cooling systems can be more precisely managed to meet real-time demand [27]. These improvements are meaningfully practical, achieving significant energy savings and thus cost savings for DCS service providers and customers. Intelligent optimization algorithms save HVAC system resources by optimizing the control strategies, manipulating control parameters and improving system performance. Intelligent control technologies dynamically adapt the HVAC system's settings and performance based on changes in indoor and outdoor conditions and user requests, improving its own capability, comfort, and cost-effectiveness.By increasing the accuracy of energy demand estimates, machine learning techniques have allowed EMS to function more pro-actively and efficiently. By concentrating on developing data-driven algorithms for short-term cooling load estimation in BDESs, [11] demonstrated the potential of machine learning approaches, including Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Extreme Gradient Boosting (XGB), in cooling load prediction. The study emphasized how attention processes are used in these models to enhance the interpretability of predictions and help operators understand how input variables—such as external temperature, humidity, and past loads relate to cooling demand. In [14] they used Artificial neural networks (ANNs) to estimate cooling demand in DCS in real-time. The ANN model was trained using operational metrics such as time of day and weather to forecast future cooling needs. The EMS reacted to changing demand patterns due to this method's ability to make more precise predictions and dynamically modify real-time data. These machine learning algorithms significantly increase the precision and reliability of demand forecasting by leveraging past data and key input parameters. This was further highlighted by [18], who used empirical demand data from specific buildings and a methodology to predict cooling flexibility for unseen structures. This bridges the gap between scattered information points and system-wide insights and is compatible with machine learning's predictive capabilities. To optimize energy usage and improve EMS performance in DCS, it is essential to integrate ML approaches, especially those that concentrate on real-time adaptability and multi-step-ahead forecasting.

(e) Artificial Intelligence Applications in Predictive Maintenance and Demand Forecasting: Predictive maintenance is the central element of the modern DCS. Therefore, through AI and sensor data, these systems are able to identify potential equipment issues before becoming significant enough to proactively make a response. This method will achieve a decrease in unscheduled downtime, without missing the extended life above the expected life span of the critical cooling infrastructure. Eventually, this will reduce the cost of the urgent repairs and component upgrades associated with the continuous delivery of the cooling services [21]. AI-powered dashboards and sensors monitor the operational conditions and system performance at all times. Thus, real-time operational insights make possible timely adjustments and proactive cooling network management towards assuring of optimum performance and reliability. With AI technology increasingly accurate and dependable in several situations, including establishing indoor thermal and humidity conditions and streamlining HVAC system operations, it also identifies equipment malfunctions due to continued optimization of algorithms.

The extensive usage of IoT sensors has made it possible to model and predict patterns in energy consumption using the data they produce. To estimate the cooling demand of buildings, Table 1 displays the coefficient of determination (R^2) performance of various models [2] used three different machine learning models were applied to forecast the TES tank's performance concerning thermocline thickness. Among the models, the K-Nearest Neighbors (KNN) algorithm achieved the highest performance with coefficient of determination (R^2) of 96.3%, followed by Artificial Neural Networks (ANNs) at 92.0%, and Support Vector Regression (SVR) at 89.0%. These results indicate that KNN was the most effective model in their study for predicting continuous variables, outperforming more complex models like ANN and SVR. [19] coupled 3 Random Forest (3RF), K-nearest neighbor (KNN), Linera Regression (LR), Random Forest (RF), General additive model (GAM), Mixed-integer linear programming (MLP). In the cooling prediction scenario, the highest-performing model in this study was 3 Random Forest (3RF), with R^2 of 97.1%, followed closely by K-Nearest Neighbors (KNN) 96.6%, General Additive Models (GAM) also showed strong performance with 96.4% , Random Forest (RF) 95.9%, Convolutional Neural Network (CNN) 92.0% , Long Short-Term Memory (LSTM) 93%, CCN-LSTM

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90.0% and Linear Regression (LR) 88.7%, . In contrast, the Mixed-Integer Linear Programming (MILP) model yielded the lowest accuracy at 77.7%, The results from this study highlight that ensemble models like 3RF and simpler, interpretable models like KNN and GAM can provide highly accurate predictions.

Predicting the short-term future need for electricity in buildings and districts is essential for optimizing energy consumption and, in turn, lowering GHG emissions. [11] discovered that LSTM and XGBoost consistently ranked among the best algorithms and offered good performance across a range of hyperparameters over 1-hour and 24-hour forecast intervals. Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGB) show excellent short-term prediction performance, each achieving an R^2 of 97.3%, whereas A-LSTM delivers the highest accuracy for long-term forecasting with an R^2 of 90.8%. Figure 1 shows the one-hour-ahead R^2 scores highlight the effectiveness of models such as XGB, LSTM, and GRU in short-term forecasting. Meanwhile, the 24-hour-ahead R^2 values provide insight into how accurately these models perform over longer prediction periods, which offers advantages in modeling complex temporal dependencies. However, their approach relies heavily on high-quality, extensive historical data.In [8], the authors used a simulation-based techno-economic optimization framework for hybrid renewable energy systems (HRES) integrating wind, solar, and geothermal resources. They achieved an overall energy efficiency of 78.5% and an exergy efficiency of 64.3%, with daily hydrogen production reaching 500 kg at a low Levelized Cost of Energy (LCOE) of \$0.085/kWh. Geothermal energy achieved the highest reliability with an exergy efficiency of 45% and the lowest LCOE (\$0.55/kWh), while wind and solar performed at lower cost-efficiency levels of \$0.72/kWh and \$0.88/kWh, respectively. A sensitivity analysis revealed that a 15% increase in wind speed boosted output by 10%, whereas a 20% drop in solar irradiance reduced output by 8%. The results revealed that simulation-driven approaches are effective for balancing energy efficiency, economic viability, and resilience in hybrid renewable systems, unlike predictive algorithms that measure model accuracy against observed data. In [9] they used only one model which is Artificial Neural Networks (ANNs) that indicates an R^2 of 94.4%. Figure 2 provides a summary of the coefficient of determination achieved by all the evaluated models. [22], compared the performance of several regression models, including Random Forest (RF), Support Vector Regression (SVR), Artificial Neural Networks (ANNs), and Linear Regression (LR). Among these, Random Forest achieved the highest accuracy at 79.2%, making it the best-performing model in their evaluation. While exact R^2 values were not provided for SVR, ANN, and LR, the study indicates that SVR performed better than ANN. However, all three were outperformed by RF. This suggests that, even though the overall accuracy levels were lower compared to the other studies, ensemble methods like RF still maintained a performance advantage over both linear and more complex nonlinear models within this dataset. Table 1 shows Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGB) achieved high coefficient of determination R^2 with values up to 97.3%.

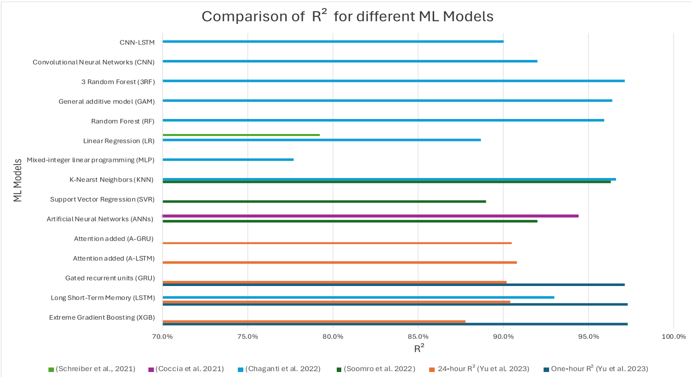

Figure 1:Comparison of R^2 for different ML Models.

In the study conducted by [19] in table 1, the predictive accuracy of several machine learning models was evaluated using Root Mean Square Error (RMSE) as the primary performance metric. The results demonstrated that the 3 Random Forest (3RF) model achieved the lowest RMSE of 0.675, indicating the highest level of accuracy among all models tested. Other models with strong performance included K-Nearest Neighbors RMSE of 1.1716, Random Forest 1.85, and the General Additive Model 1.863, all of which maintained RMSE values under 2.0. Deep learning models such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) yielded RMSEs of 2.41 and 2.69, respectively, reflecting moderate accuracy. The CNN-LSTM hybrid model recorded an RMSE of 2.89, while Linear Regression showed the highest error with an RMSE of 3.106.

Table 1:Comparison of Different Machine Learning Tools for Cooling Load Prediction.

Study	ML Model	Task Type	Forecast Horizon	Metric	Value
[2]	Artificial Neural Networks (ANNs)	Regression	N/A	R^2	92.0%
[2]	Support Vector Regression (SVR)	Regression	N/A	R^2	89.0%
[2]	K-Nearst Neighbors (KNN)	Regression	N/A	R^2	96.3%
[19]	Mixed-integer linear programming (MLP)	Regression	N/A	R^2	77.7%
				RMSE	4.672
[19]	K-nearst neighbors (KNN)	Regression	N/A	R^2	96.6%
				RMSE	1.1716
[19]	Linear Regression (LR)	Regression	N/A	R^2	88.7%
				RMSE	3.106
[19]	Random Forest (RF)	Regression	N/A	R^2	95.9%
				RMSE	1.85
[19]	General additive model (GAM)	Regression	N/A	R^2	96.4%
				RMSE	1.863
[19]	3 Random Forest (3RF)	Regression	N/A	R^2	97.1%
				RMSE	0.675
[19]	Convolutional Neural Networks (CNN)	Regression	N/A	R^2	92.0%
				RMSE	2.69
[19]	Long Short-Term Memory (LSTM)	Regression	N/A	R^2	93.0%
				RMSE	2.41
[19]	CNN-LSTM	Regression	N/A	R^2	90.0%
				RMSE	2.89
[11]	Extreme Gradient Boosting (XGB)	Regression	1-hour ahead	R^2	97.3%
				RMSE	0.1451
[11]	Long Short-Term Memory (LSTM)	Regression	1-hour ahead	R^2	97.3%
				RMSE	0.1464
[11]	Gated recurrent units (GRU)	Regression	1-hour ahead	R^2	97.1%
				RMSE	0.151
[11]	Extreme Gradient Boosting (XGB)	Regression	24-hour ahead	R^2	87.8%
				RMSE	0.3055
[11]	Long Short-Term Memory (LSTM)	Regression	24-hour ahead	R^2	90.4%
				RMSE	0.2712
[11]	Gated recurrent units (GRU)	Regression	24-hour ahead	R^2	90.2%
				RMSE	0.2738
[11]	Attention added (A-LSTM)	Regression	24-hour ahead	R^2	90.8%
				RMSE	0.2661
[11]	Attention added (A-GRU)	Regression	24-hour ahead	R^2	90.5%
				RMSE	0.2697
[1]	Artificial Neural Networks (ANNs)	Regression	N/A	R^2	94.4%
[10]	Light Gradient Boosting Machine (LightGBM)	Regression	N/A	RMSE	0.135
[10]	Long Short-Term Memory (LSTM)	Regression	N/A	RMSE	0.176
[22]	Random Forest (RF)	Regression	N/A	R^2	79.2%

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While in [11] the Root Mean Square Error (RMSE) metric for evaluated for both 1-hour and 24-hour ahead forecasting of cooling load allows for comparison of prediction errors among various machine learning models. For the 1-hour ahead prediction, Extreme Gradient Boosting (XGB) achieved the lowest RMSE of 0.1451, followed closely by Long Short-Term Memory (LSTM) with 0.1464, and Gated Recurrent Units (GRU) with 0.151, reflecting high short-term prediction accuracy across all three models. In the 24-hour ahead forecasting scenario, RMSE values were slightly higher, as expected for longer prediction horizons. XGB recorded an RMSE of 0.3055, while LSTM and GRU models achieved 0.2712 and 0.2738, respectively. The incorporation of attention mechanisms further improved the performance of machine learning models, with Attention-LSTM and Attention-GRU achieving RMSE values of 0.2661 and 0.2697, indicating enhanced long-term forecasting accuracy and learning efficiency. Additionally, in [10] Light Gradient Boosting Machine (LightGBM) demonstrated superior prediction performance with an RMSE of 0.135, outperforming LSTM, which recorded an RMSE of 0.176. Figure 2 presents a comparison of RMSE values across various machine learning models, reinforcing the findings in Table 1. It highlights that LightGBM and LSTM achieved higher predictive accuracy, with a lower RMSE indicating better performance.

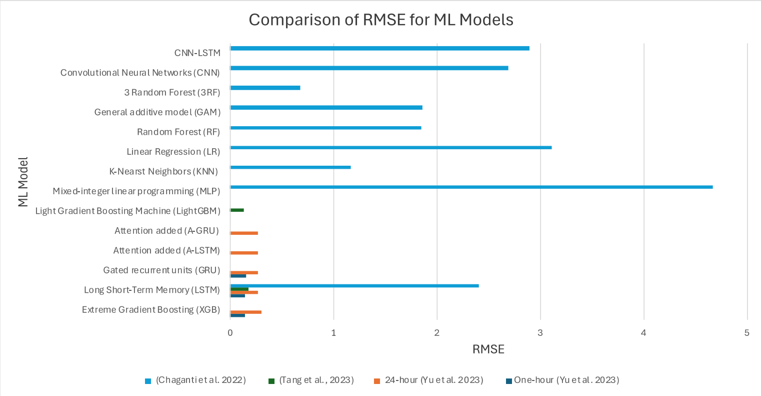

Figure 2: Comparison of RMSE for different ML Models.

These studies provide valuable insights into ML performance, many rely on static datasets and limited feature engineering, which may not reflect real-time system dynamics in DCS operations. For instance, although models like 3RF and KNN showed high R² values, they may be sensitive to overfitting and lack generalizability across different cooling systems. Deep learning models such as LSTM and CNN, while powerful, often require large volumes of training data and can be computationally intensive. Additionally, few studies have assessed long-term model stability or adaptability under varying climatic conditions, which is crucial for practical EMS applications.

To detect abnormalities in both ducted-centralized and ductless-split cooling systems, [13] suggest a three-stage, non-invasive part-level identification approach that uses COTS sensors to track energy use and temperature without penetrating the cooling system. If the compressor in the cooling system malfunctions, Nearest-Neighbors Density-Based Spatial Clustering of Application with Noise NN-DBSCAN which is used to enhance clustering, especially in large or complex data set and provides notable energy savings.

3) Methods and Methodology

Depending on the literature review conducted, it was observed that the authors used different predictive modeling and improvement methods to enhance the performance of EMS in DCS. The existing studies have evaluated different parameters in the context of energy efficiency in DCS. However, limited studies have considered the role of pump inlet and outlet pressure, time of day, day of the week, seasonal, historical load data, building thermal gains, and humidity which are essential for making EMS more effective in district cooling operations.

Different AI tools have varying coefficient of determination (R^2) , determining their widespread use in improving EMS performance in DCS. Table 1 shows the prevalence of AI tools in the existing knowledge base.

This study aims to assess the effectiveness of the existing Energy Management System (EMS) in a District Cooling Plant operated by a UAE-based company that plays a role in developing and managing infrastructure and real estate projects across the UAE. It operates through several departments that focus on different areas such as hospitality, retail, real estate, and utilities. This research focuses specifically on the department responsible for managing District Cooling Plants (DCPs), which play a key role in providing efficient cooling services to buildings and communities.

As part of this case study, the research will analyze three District Cooling Plants (DCPs) under a UAE-based company's operations:

1. District Cooling Plant A.
2. District Cooling Plant B.
3. District Cooling Plant C.

These plants will be studied in detail to assess the current performance of their Energy Management Systems (EMS), identify areas for improvement, and test AI-based enhancements. The UAE-based company's strong focus on sustainability and digital innovation supports this research by providing access to real operational data and the opportunity to propose real-world improvements. Using historical operational data from 2022 to 2024, specifically electricity consumption (kWh), chilled water production (TR-hr), and kW/TR ratio and the engineered features derived from this dataset. The research will develop machine learning-based predictive model LSTM to forecast long-term cooling demand. This model will incorporate all relevant features detailed in the feature engineering section of the study, considering temporal patterns, lag effects, trends, and variability. The performance of the model will be evaluated using metrics like RMSE, R^2, MAPE, and MAE, with cross-validation applied to ensure model reliability and robustness. Insights from the analysis will be used to recommend EMS improvements aimed at boosting energy efficiency and operational reliability. These enhancements will then be tested through a pilot testing to validate their impact on reducing costs, increasing efficiency, and improving overall system performance.

(a) Data Collection Process

The methodology of this research involves developing predictive models using historical operational data from three different District Cooling Plant under a UAE-based company: District Cooling Plant A, District Cooling Plant B, and District Cooling Plant C. The data collection focus on both internal system performance and external influencing factors, covering the years 2022 to 2024. The models aim to forecast long-term energy and cooling demand and improve operational efficiency of the chillers in real time. Data is extracted from the Building Management System (BMS), control systems, and BTU meters at daily intervals, as shown in Figure 3, aligning with the scope of the dataset described in the study. To enhance prediction accuracy and operational insight, the data includes numerous features engineered from the original data, such as temporal features (e.g., day of the year, month, day of the week, weekend indicator), lag features (previous day's consumption values), exponential moving averages (7, 14, 30 days), rolling statistics (standard deviation, max, min), and trend indicators (day-to-day and week-to-week changes). The engineered features derived from the existing dataset are designed to support model robustness, improve fault detection, and increase energy efficiency.Missing data is addressed using linear interpolation for short gaps and forward/backward filling for longer gaps. All data undergoes preprocessing steps involves converting raw CSV strings into numerical arrays so they can be used in analysis. During this step, the data is checked for missing or invalid values. If any missing data is found, it is handled by filling in with estimates or removing those data points, ensuring the dataset is complete and accurate for building the model.Given the sophisticated model architecture, attention has been given to feature importance, relationships between variables are analyzed to detect multicollinearity. Highly correlated features are either combined or reduced to ensure model efficiency and accuracy. The engineered features, such as lag variables, moving averages, and cyclical encodings, are designed to capture complex temporal patterns and seasonal variations useful for the Long Short-Term Memory (LSTM) models employed. This data collection and preprocessing strategy creates a strong foundation for building accurate models to improve energy management and operational efficiency.

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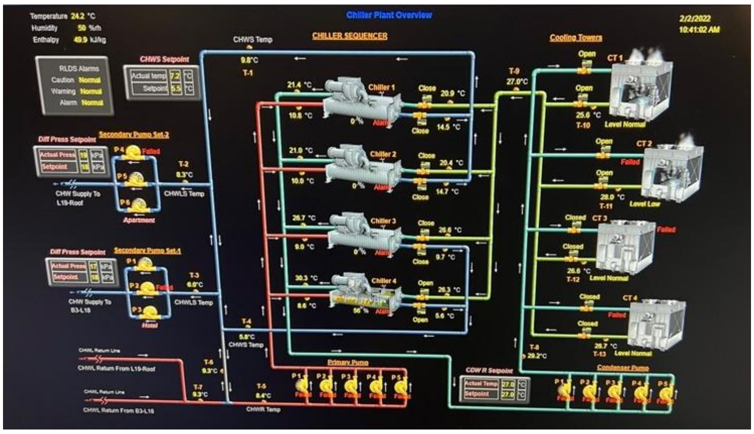

Figure 3: Control System

(b) Model Selection

Based on the literature review and prior comparative studies, the Long Short-Term Memory (LSTM) model is selected for 24-hour-ahead forecasting of energy consumption, chilled water production (cooling load), and system demand to support daily energy planning. We have chosen a sophisticated hybrid model called the Transformer-LSTM because it is highly effective at understanding complex, time-based data patterns, which is essential for predicting energy demand. This model combines two powerful techniques: the Transformer encoder and bidirectional LSTM layers. The Transformer component allows the model to analyze all past days simultaneously, paying more attention to the most relevant days, for example: hot summer days when energy use is higher. Overall, this hybrid approach enables us to capture seasonal, operational, and contextual patterns unique to the UAE weather more effectively than simpler models, making it ideal for the complex task of predicting long-term energy demand in the district cooling system. Compared to models like GRU or XGBoost, LSTM demonstrates a stronger ability to capture long-term dependencies without losing past contextual information. An initial pilot test will be conducted to benchmark LSTM's performance against GRU and XGBoost to confirm its suitability for the UAE context.

(c) Model Training and Evaluation

To simulate real-world forecasting performance, the models was trained on historical data from 2022 to 2024 and tested on data from 2025. Specifically, 85% of the (covering January 2022 to December 2024) was used for training, while the remaining 15% was reserved for validation. Python tools like pytorch was used to train and test the model. The final model was evaluated on the 2025 data to assess its ability to generalize to future conditions.

For LSTM models, a yearly prediction approach was used. The model learned from feature engineering and operational input patterns in a specific month of 2022, 2023, or 2024 (e.g., March 2022, 2023, or 2024) and predict the corresponding energy consumption, chilled water production (cooling load), and efficiency (KW/TR) for the same period in 2025 (e.g., March 2025). This approach is designed to capture seasonal and operational patterns that repeat annually, improving the model's ability to forecast future performance in a realistic setting.

To achieve accurate results, three separate LSTM-based models were developed, each dedicated to a specific metric:

- Electricity consumption (kWh)
- Chilled Water Production (TR-hr)
- kW/TR ratio (efficiency).

This separation was necessary because each metric shows different operational patterns and scales. For instance, electricity consumption may depend on different influencing factors compared to kW/TR efficiency, requiring the use of slightly different input features. Training independent models for each metric allowed parameter fine-tuned specific to the target variable, leading to more accurate and reliable predictions. As a result, the use of three dedicated models provided better overall performance than a single multi-output model.

The forecasting model was designed as a hybrid Transformer-LSTM model rather than a simple 1–2-layer LSTM. It consists of 9 layers. Layer 1:an input-projection layer that transformed the feature engineering input into a higher-dimensional form (256 neurons) so the model could learn better from the patterns in the data. Layer 2: a Transformer encoder with four self-attention heads which can analyze all 45 days simultaneously and determine which days are most important. Layer 3: Bidirectional LSTM Reads data sequences in both forward and backward directions, starting with 256 neurons and gradually reducing to 128, allowing the model to capture time-based relationships more accurately. Dropout is applied here to prevent overfitting. Layer 4: a multi-query attention highlights the most relevant patterns learned by the LSTM. Layer 5: Residual connection implements a skip connection from the input to the LSTM output, helping the model maintain stable gradient flow and prevent the vanishing gradient problem during training. Layers 6-9: Fully connected layers passing through four fully connected layers with 128, 64, 32, and finally 1 neuron, producing the final prediction. To improve the model's accuracy and prevent overfitting, dropout was applied to randomly turn off some neurons during training. The model parameters, such as the initial learning rate (0.001), number of epochs how many times it should train (maximum 150), the learning rate, and batch size (32), were developed using advanced training techniques such as learning rate warmup that gradually increases learning rate from 0 to 0.001, ReduceLROnPlateau scheduling which reduce learning rate by 50% if validation loss doesn't improve for 12 epochs, label smoothing loss adds small penalty (0.05) to prevent overconfidence, gradient clipping limits gradient to maximum norm of 1 to prevent exploding gradients in deep networks, early stopping is applied to stop training when the model is no longer improving, helping save time and avoid overfitting, stochastic weight averaging after 50% of training, averages model weight from multiple epochs for better generalization, and data augmentation to achieve the best performance.

Model's validation was conducted through a pilot testing, based on real data from a UAE-based company's district cooling plants. The models predict cooling load, energy use, and KW/TR efficiency for long-term prediction. Prediction results were compared with the actual 2025 values evaluate forecasting accuracy and the EMS's ability to support operational improvement.

Performance will be evaluated using:

- Coefficient of Determination (R^2).
- Mean Absolute Percentage Error (MAPE).
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE).

These metrics provided a comprehensive understanding of model accuracy and reliability in forecasting energy consumption and cooling load.

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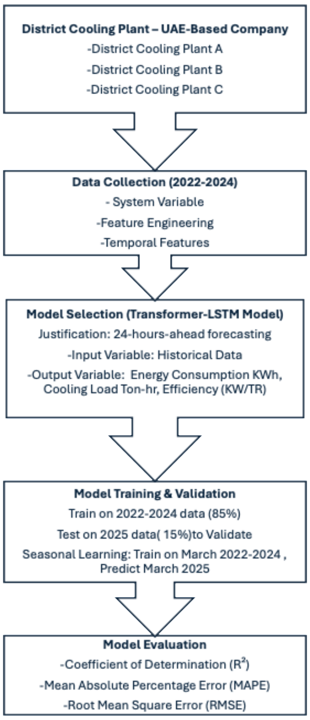

Figure 4:Methodology, UAE-Based Company Case Study Flowchart.

4) Result and Discussion

(a) Comparative Analysis of Predictive Models

The initial phase of the model evaluation involved comparison of three predictive models, Transformer-LSTM (hybrid deep learning), GRU (gated recurrent unit), and XGBoost (extreme gradient boosting), using historical operational data from District Cooling Plant A. This initial pilot testing shown in Figure 5 was conducted to identify the model best suited for forecasting electricity consumption (Kwh), chilled water production (Ton-hr), and the efficiency (KW/TR) within the UAE-based district cooling context.The LSTM model, designed for sequential time-series data, served as the baseline for comparison. The Transformer-LSTM model, which combines the long-term memory capability of LSTM with the attention mechanism of the transformer architecture to identify relevant past data simultaneously, while bidirectional LSTM captures sequential dependencies in both forward and backward directions improving the accuracy of time-series predictions. Residual connections ensure stable training by preventing vanishing gradient and demonstrated the strongest overall performance across all metrics. Compared to simpler models like GRU, which have quicker training times but less expressive capacity and no separate memory cell, and XGBoost, which treats data points independently without capturing sequential and temporal dependencies resulting in significantly lower accuracy for time series data, the Transformer-LSTM offers superior performance in modeling long-term dependencies and seasonal patterns essential for accurate long-term predictions.

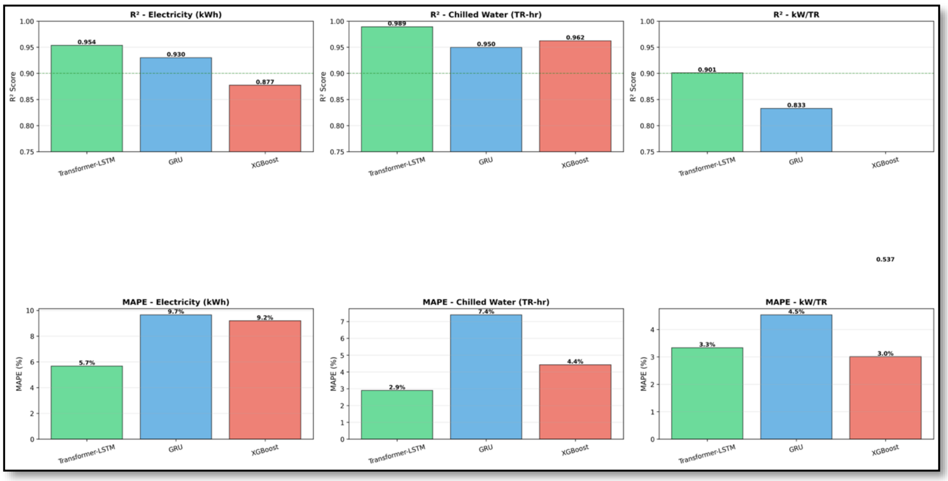

Figure 5:Performance Comparison between Transformer-LSTM, GRU, and XGBoost Models

Table 2: Comprehensive Comparison Results of Transformer-LSTM, GRU, and XGBoost

Metric	Model	R²	RMSE	MAPE
Electricity (kWh)				
	Transformer-LSTM	0.9537	2313.92	5.68%
	GRU	0.9302	2842.63	9.66%
	XGBoost	0.8773	3825.19	9.19%
Chilled Water (TR-hr)				
	Transformer-LSTM	0.9894	1203.48	2.90%
	GRU	0.9498	2614.92	7.40%
	XGBoost	0.9625	2173.29	4.42%
kW/TR				
	Transformer-LSTM	0.9009	0.05	3.33%
	GRU	0.8328	0.06	4.53%
	XGBoost	0.5374	0.04	3.00%

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Table 3: Average Comparison Performance Across all Metrics of Transformer-LSTM, GRU, and XGBoost

Model	Avg R²	Avg MAPE
Transformer-LSTM	0.9480	3.97%
GRU	0.9043	7.20%
XGBoost	0.7924	5.54%

(b) Models Performance and Accuracy

Using the optimized Transformer-LSTM model trained on historical data from District Cooling Plant A from (January 2022 to December 2024), a 365-day forecast was generated for electricity consumption (Kwh), chilled water production (Ton-hr), and system efficiency (KW/TR) was generated for the year 2025. Each parameter was predicited using a separte Transformer-LSTM model to improve accuracy and flexibility. The three metrics electricity consumption, chilled-water production, and kW/TR efficiency have different scales and patterns, so separate models gave better results. When tested, the multi-output model showed a 3–5% lower R^2 for all metrics, confirming that individual models performed better. This long-term prediction provides valuable insights for operational planning and energy management within the district cooling system.

vely affirm the model's suitability for long-term energy demand forecasting within this context. Collectively, these results indicate that the three Transformer-

Table 4: Final Performance Metrics of the Transformer-LSTM Models

Metric	R² Score	MAPE	Interpretation
Electricity Consumption (Kwh)	0.9569	5.71%	Excellent
Chilled Water Production (Ton-hr)	0.9878	3.38%	Outstanding
kW/TR (Efficiency)	0.9009	3.59%	Excellent

These high-performance metrics indicate that the models provides accurate forecasts, enabling proactive operational decisions and efficient energy management strategies for the upcoming year.

(c) Models Predictions for Individual (different) District Cooling Plants

This section presents the results of the model evaluation across the three District Cooling Plants (A, B, and C). The purpose of this analysis is to improve the model's adaptability, generalizability, and accuracy under different operational conditions. Each plant data was analyzed individually to identify performance variations, influencing factors, and model improvement opportunities.

1. District Cooling Plant A

Selected as the primary reference site, the Transformer-LSTM models showed strong agreement between predicted and historical values across all three performance metrics: electricity consumption (Kwh), chilled-water production (Ton-hr), and system efficiency (kW/TR). The predictions successfully captured the plant's seasonal operating cycles, with clear peaks during the summer months (June–August) and lower loads in winter (December–February).
This strong correlation indicates that the model effectively learns the feature engineering including the seasonal demand dynamics on electricity and chilled-water consumption. Overall, the model achieved high accuracy and generalization ability, producing results closely aligned with actual operational data.
Annual Totals for District Cooling Plant A:

- Electricity Consumption: 8,809,116 kWh
- Chilled-Water Production: 10,848,723 TR-hr
- Average System Efficiency: 0.88 kW/TR

Uncertainty quantification using 95% confidence intervals further validated the reliability of the model's forecasts. The majority of predicted values fell within these intervals, confirming a high level of confidence in the model's long-term prediction stability.
Figures 6–8 illustrate monthly comparisons of electricity consumption, chilled-water production, and system efficiency for the years 2022–2025, highlighting the close alignment between actual historical and predicted values for 2025.

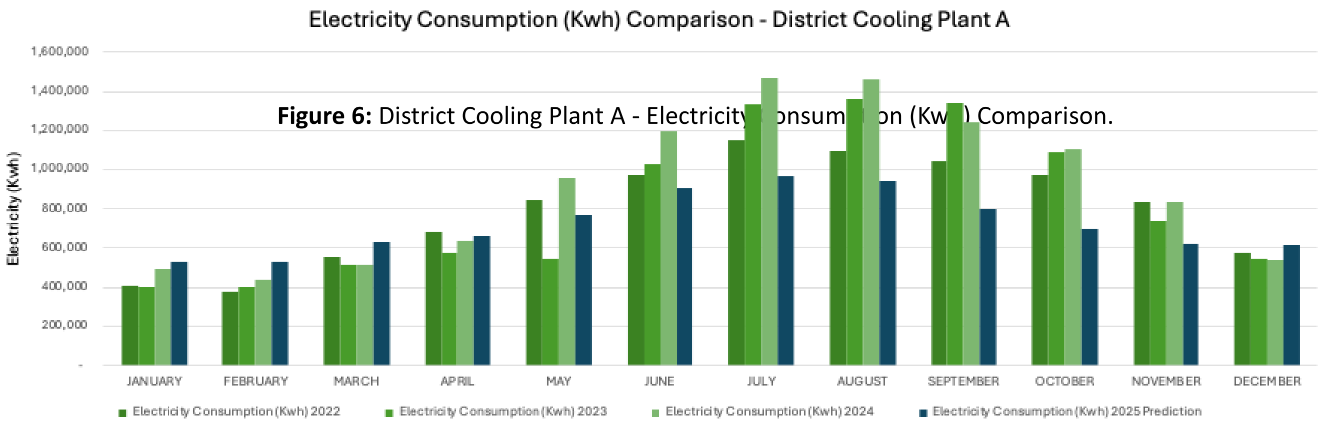

Figure 6: District Cooling Plant A - Electricity Consumption (Kwh) Comparison.

Figure 7: District Cooling Plant A - Chilled Water Production (Ton-hr) Comparison.

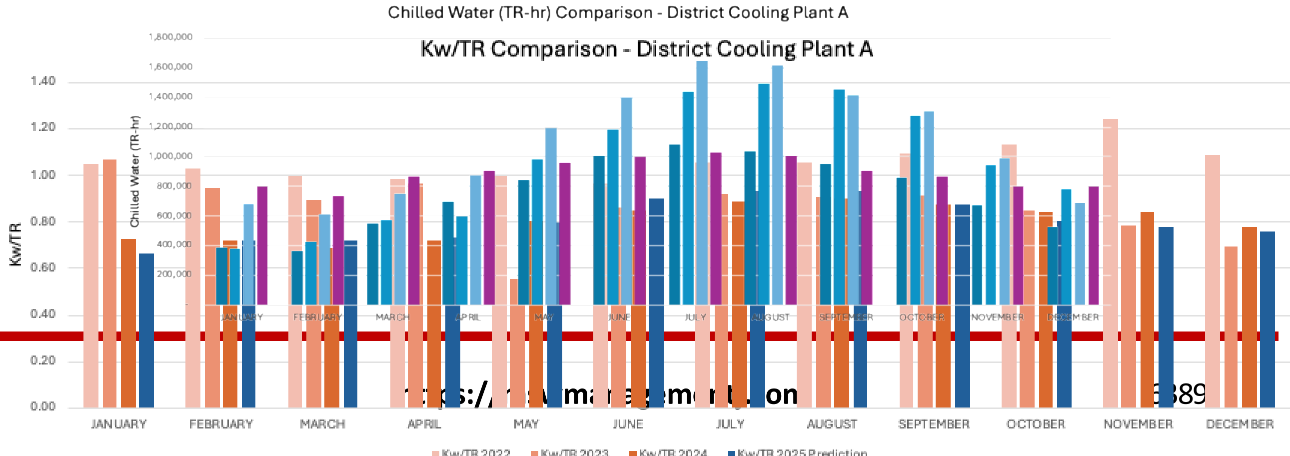

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Figure 8: District Cooling Plant A - Efficiency KW/TR Comparison.

2. District Cooling Plant B

Data from District Cooling Plant B showed higher fluctuations in energy consumption and chilled water production (cooling demand) compared to District Cooling Plant A, reflecting normal operational variations and measurement fluctuations within the plant's performance data. To improve prediction accuracy, the Transformer-LSTM model benefited from the feature, such as lag values, rolling averages, and trend indicators, which helped capture recurring daily and seasonal patterns more effectively.

The model effectively captured both seasonal and short-term load variations, with the 2025 predictions following similar trends observed in previous years. Monthly results indicate a steady rise in electricity consumption and chilled water production during the summer months (June–August), followed by lower consumption during the cooler winter period.

Annual Totals for District Cooling Plant B:

- Electricity Consumption: 10,891,237.10 kWh
- Chilled-Water Production: 9,640,282.64 TR-hr
- Average System Efficiency: 0.99 kW/TR

Uncertainty quantification using 95 % confidence intervals (CI) further validated prediction reliability, with uncertainty margins of ± 3,535.96 kWh for electricity, ± 3,123.43 TR-hr for chilled water, and ± 0.03 for kW/TR. These narrow intervals indicate high model confidence and minimal variability between predicted and actual operational values.

Figures 9–11 present monthly comparisons of electricity consumption, chilled-water production, and system efficiency for 2022–2025, showing the close agreement between the model's forecasts and historical performance patterns.

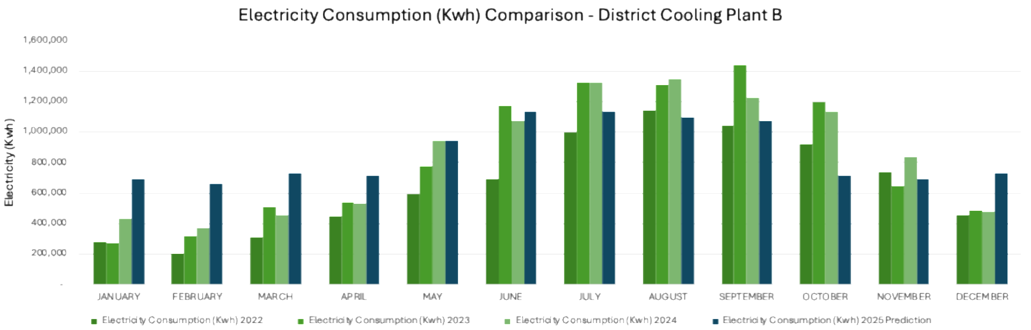

Figure 9: District Cooling Plant B - Electricity Consumption (Kwh) Comparison.

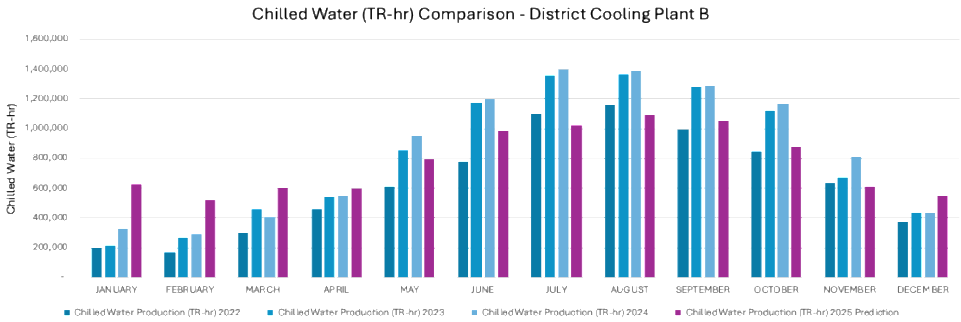

Figure 10: District Cooling Plant B - Chilled Water Production (Ton-hr) Comparison.

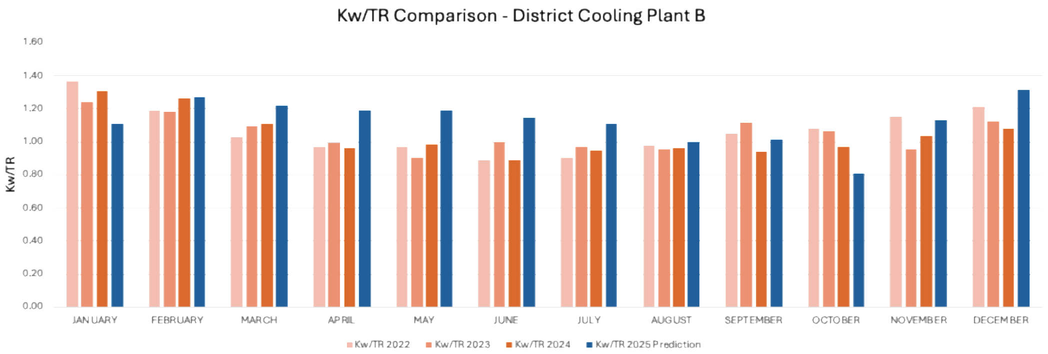

Figure 11: District Cooling Plant B - Efficiency KW/TR Comparison.

3. District Cooling Plant C

Data from District Cooling Plant C were generally similar to those of Plant A, but the model was trained and tested using only two years of data (2023–2024). This shorter period limited the model's ability to capture full seasonal and long-term patterns compared to Plants A and B. Even with this limitation, the Transformer-LSTM model was able to learn the plant's operating trends and predict future energy and cooling demand with good accuracy.

The model successfully forecasted most of the monthly demand patterns, with minor deviations in some months likely caused by variations in the historical data. These results suggest that the differences in prediction accuracy are mainly due to the shorter data period available for model training. With a longer historical dataset, the model could capture more seasonal patterns and further improve its reliability.

Annual Totals for District Cooling Plant C:

- Electricity Consumption: 3,382,269.82 kWh
- Chilled-Water Production: 2,778,382.86 TR-hr
- Average System Efficiency: 0.75 kW/TR

Uncertainty (95% Confidence Interval):

- Electricity: ± 1,223.90 kWh

- Chilled Water: ± 1,396.92 TR-hr
- kW/TR: ± 0.02

These small uncertainty values indicate that the model's forecasts were stable and dependable even with a shorter dataset. Figures 12–14 show monthly comparisons of electricity use, chilled-water production, and system efficiency for 2023–2025, where the predicted 2025 values align closely with historical performance trends.

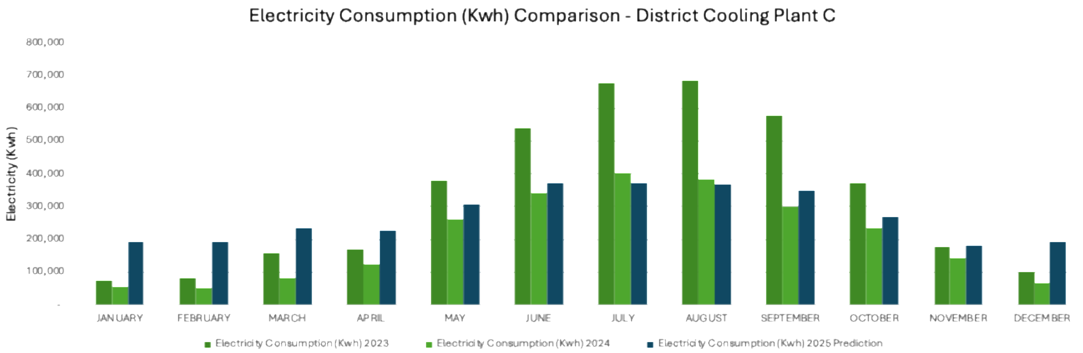

Figure 12: District Cooling Plant C - Electricity Consumption (Kwh) Comparison.

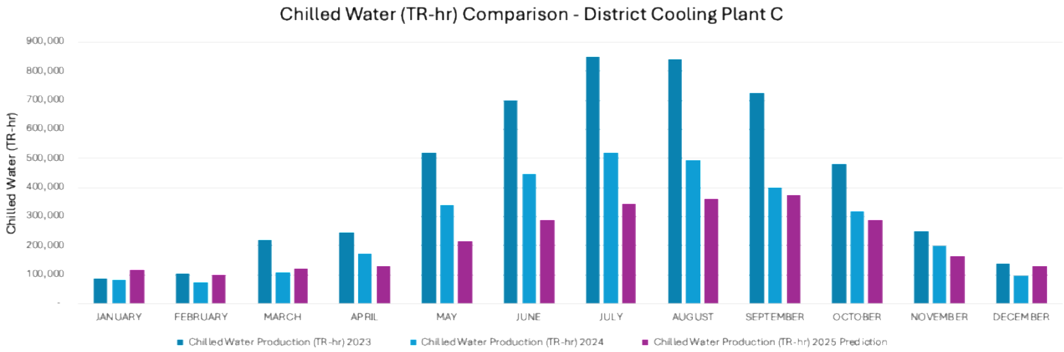

Figure 13: District Cooling Plant C - Chilled Water Production (Ton-hr Comparison.

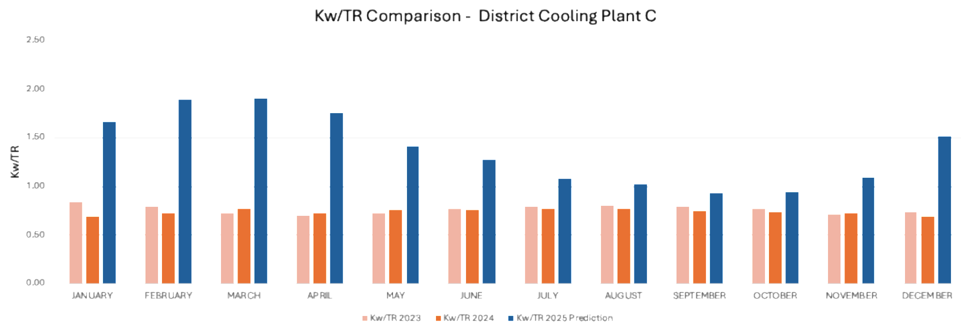

Figure 14: District Cooling Plant C - Efficiency KW/TR Comparison.

5) Conclusion

This study evaluated the current Energy Management Systems (EMS) performance in three district cooling plants and developed a forecasting framework using a hybrid Transformer-LSTM architecture trained on historical operational data from 2022 to 2024. Across electricity consumption, chilled-water production, and kW/TR efficiency, the proposed model consistently outperformed GRU and XGBoost, achieving high accuracy, with R^2 around 0.95 and errors less than 6%. Uncertainty analysis (95% CI) indicated stable and reliable predictions.

At the plant level, the forecasting results closely matched the actual operational patterns. Plant A served as the reference point, where the model accurately captured both seasonal peaks and low-demand periods. Plant B showed more variability, but the inclusion of engineered features such as time lags, rolling averages, and trend indicators helped achieve stable and reliable predictions with narrow confidence intervals. Plant C, trained on a shorter two-year dataset, still produced consistent forecasts. However, minor deviations highlight the importance of using longer historical data to better capture complete seasonal behavior. Overall, separating the models for electricity use, chilled-water production, and efficiency improved prediction accuracy and provided useful insights for operation. These forecasts can support proactive decisions, such as improving chiller scheduling, adjusting setpoints in advance, and identifying deviations. When applied, this approach can help reduce energy consumption, smooth demand peaks, and enhance system efficiency,contributing to more sustainable and cost-effective cooling operations. Moreover, the study supports the UAE's broader sustainability goals, including the UAE Clean Energy Strategy 2050, by promoting smarter energy use in key infrastructure. Ultimately, this study contributes to the advancement of sustainable energy management practices across the UAE.

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8) **Data Availability:**

Data sharing is not applicable to this article.

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