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PETRONAS-UTP 5G LAB DEVELOPMENT

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ABSTRACT

This research explores the integration of 5G technology, virtual reality (VR), augmented reality (AR), and dynamic modelling to revolutionise industrial processes and foster economic growth. With Malaysia's adoption of 5G technology and Petronas' pioneering efforts in deploying commercial private networks, the transformative potential of these technologies becomes evident. Collaborative endeavours between the government, the private sector, and academia drive innovation. At the same time, integration with the Internet of Things (IoT), artificial intelligence (AI), and automation promises enhanced operational efficiency and safety. Petronas, a major energy industry player, benefits from 5G's applications in optimising operations and improving safety protocols. The research highlights the synergy between 5G, VR, AR, and dynamic modelling, offering insights into their potential to enhance industrial processes, promote sustainability, and stimulate innovation. The proposed LSTM approach gained 35% reduction time using transfer learning as compared to periodic training with 15%. However, the RMSE of LSTM was observed to be 0.42, for periodically retrained LSTM it was 0.36, whereas for LSTM with transfer learning was 0.29.

Keywords: *5G technology, oil & gas industry, dynamic modelling, virtual reality, augmented reality*

INTRODUCTION

Malaysia's launch of 5G technology in 2021 heralded a new era of connectivity, particularly beneficial for its vast SME sector, which comprises 97.4% of businesses in the country [1]. Petronas' pioneering use of commercial private 5G networks, notably at RGTSU in Melaka, demonstrates the commitment of leading companies to embrace technological advancements (Figure 1). Collaborative efforts between the government, private sector, and academia are driving innovation and talent development, essential for maintaining Malaysia's competitiveness. With the goal of achieving 80% 5G network coverage by 2023, Malaysia is poised to leverage this technology's transformative potential across diverse industries. Integration with the Internet of Things (IoT), artificial intelligence (AI), and automation promises to revolutionise operational efficiency and safety standards, particularly in sectors like sustainable energy solutions [2].

Petronas, a major energy industry player, is poised to benefit from 5G technology's wide-ranging applications, including optimising oil and gas operations with IoT sensors, enhancing safety protocols through real-time data analysis, and improving remote team communication. Integration of dynamic models into the operator training system (OTS) using virtual reality (VR) and augmented reality (AR) aims to improve efficiency and safety within Petronas facilities [3]. Challenges like delays in accessing data from the distributed control system (DCS) are being tackled through direct engagement with plant operation teams for streamlined data acquisition [4]. Integrating dynamic modelling with 5G communication promises to enhance industrial efficiency and reliability by enabling real-time dynamic modelling in processes. AR and VR technologies further enhance process control optimisation by facilitating immersive training simulations and enabling predictive maintenance through advanced data analytics [5].

Figure 1 5G Petronas installation at selected operating units

5G INFRASTRUCTURE

Private 5G Network Architecture

A distributed core architecture with 5G Enterprise Core on-premises is chosen for this private 5G network due to several key advantages. This architecture enhances security by isolating data from external networks, protecting sensitive operational information and preventing unauthorised access. It also provides granular control over network configuration, quality of service (QoS), and security policies, allowing for precise optimisation to meet specific operational requirements. Additionally, Distributed Core offers scalability, enabling flexible capacity expansion to accommodate future growth and the addition of new devices and applications. Finally, the smaller, more manageable equipment associated with this architecture simplifies integration into existing infrastructure, reducing complexity and streamlining deployment, as well as optimising cost for deployment as its scall can be sized to the facility as opposed to public 5G deployment, which is on a much larger scale to cater for mass consumer consumption.

Network Segmentation: Separate APNs for IT and OT

Network segmentation is implemented by using separate access point names (APNs) for information technology (IT) and operational technology (OT) traffic, enhancing security and optimising performance. This segmentation aligns with the Purdue Model for industrial control system security, where different levels of the operational network are isolated to minimise risk. In this private 5G deployment, process monitoring data contributes to the operational process and is segregated into a distinct APN. This ensures priority handling for these time-sensitive communications and isolates them from less critical IT traffic like email and internet browsing. This level of segmentation bolsters the overall security posture, reducing the attack surface and minimising the potential impact of a security breach. Furthermore, by prioritising OT traffic, the network ensures reliable and responsive communication for real-time monitoring and control, which is essential for maintaining safety and operational efficiency in the oil and gas industry.

5G FWA for “Air Fibre” Connectivity

5G fixed wireless access (FWA) or customer premise equipment (CPE) provides “air fibre” connectivity to field auxiliary rooms (FARs), substations, and metering stations. This eliminates complex and costly fibre optic installations in challenging oil and gas environments, improving deployment speed and reducing operational expenses.

RELATED WORK

Model drift, a significant challenge in machine learning for industrial applications, has been extensively studied in various domains. Basseville and Nikiforov [1] proposed methodologies for detecting abrupt changes in data, highlighting the importance of adaptive models to maintain accuracy. More recently, ensemble methods and transfer learning have been explored to mitigate drift effects. The integration of LSTM models in industrial settings has demonstrated promising results in handling time-series data, particularly for predictive maintenance and process optimisation [2]. Studies have also emphasised the role of 5G technology in enhancing real-time data transmission, enabling faster adaptation to dynamic process conditions [3].

Accurate short-term load forecasting (STLF) is crucial for maintaining a stable and efficient power grid. However, traditional forecasting techniques struggle to adapt to evolving electricity consumption patterns due to concept drift (CD). CD manifests when the relationship between input factors and electricity demand shifts over time, making conventional models ineffective. Researchers categorise CD into four main types: sudden, gradual, incremental, and recurring [5]. Several methods have been proposed to handle CD, including online learning, ensemble-based techniques, and drift detection mechanisms that trigger model retraining [6]-[7]. However, many of these techniques have limited applications in STLF.

Within online learning, methods such as online support vector regression (OSVR) [6] and online adaptive RNN [8] have demonstrated moderate success. Fekri and Jagait [8] introduced an RNN-ARIMA hybrid approach to address CD, while Liang and Ceci [9] proposed daily neural network retraining to adapt to evolving data patterns. While these models improve forecasting performance, they often rely on extensive retraining, which is computationally expensive [9].

More recent studies, such as Azeem et al. [10], introduced an adaptive ensemble LSTM (AE-LSTM) framework to mitigate CD effects in smart grids by employing dynamic feature engineering [10]. Another significant advancement is the transfer learning adaptive LSTM (TLA-LSTM) model, which leverages pre-trained representations [10] to improve model adaptability [9]. The TLA-LSTM framework demonstrated superior forecasting accuracy across diverse CD scenarios, including concept expansion (CEXP) and concept evolution (CEVO). Unlike traditional approaches, TLA-LSTM dynamically detects and adapts to CD without requiring full model retraining, making it highly effective for real-time applications.

The integration of 5G technology further enhances STLF by enabling high-speed, low-latency data transmission, ensuring seamless real-time updates to predictive models [3]. Unlike conventional network architectures, private 5G infrastructures provide greater control over data security, reliability, and bandwidth allocation, making them ideal for industrial applications [11]. In particular, network slicing and edge computing capabilities within 5G networks enhance model responsiveness by reducing the computational load on central processing units.

AR and VR applications provide additional advantages in STLF by offering interactive visualisation of model deviations and real-time data monitoring [2]. These technologies enable operators to engage with predictive models intuitively, improving decision-making processes [1]. For example, an AR-assisted operator training system can provide real-time insights into load variations, while VR simulations can demonstrate the impact of CD on forecasting accuracy [9]. Integrating AR/VR with 5G ensures that model adaptations occur with minimal latency, further reinforcing system reliability [3].

Our research extends previous work by incorporating 5G-enabled real-time model adaptation and AR/VR-based monitoring to improve STLF accuracy. By integrating these advanced technologies with LSTM-based forecasting models, we enhance the robustness and efficiency of predictive analytics in industrial settings. The proposed framework detects and adapts to CD and optimises industrial operations through seamless data integration, real-time visualisation, and enhanced decision-making capabilities.

MATERIALS AND METHODS

Development Dynamic Modelling

The process begins with carefully selecting the study's process area (Figure 2). It is followed by the development of a dynamic simulation using Aspen HYSYS and a mathematical model constructed using first-principle techniques. Comparing the outputs from the simulation, mathematical model, and system identification helps assess their congruence and identify disparities, with drift serving as a criterion for model adaptation using transfer learning techniques.

In the subsequent phase, all collected data will be transmitted and retrieved through a REST API, utilising the high-speed and low-latency capabilities of 5G technology within the Universiti Teknologi PETRONAS (UTP) environment. This seamless data exchange enables real-time monitoring and analysis. At the same time, integration with a VR headset provides immersive visualisation and interaction, enhancing user experience and facilitating deeper insights into system dynamics

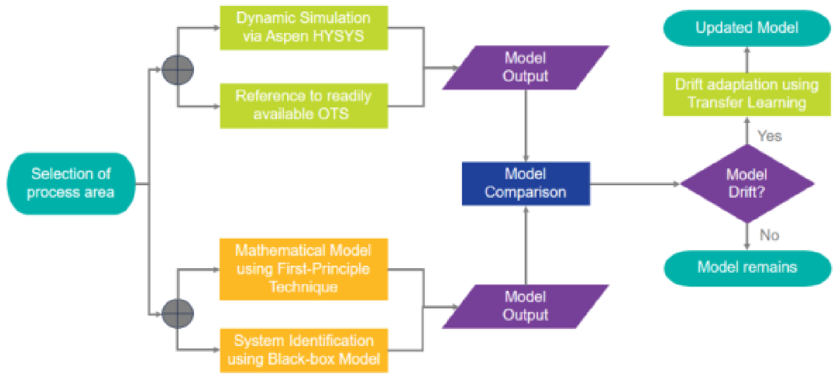


Figure 2 Flowchart of the data stream to forecast using transfer learning

for more informed decision-making and optimisation strategies.

Algorithm for Applied Model

This algorithm is developed based on methodologies discussed in prior works, particularly AE-LSTM and TLA-LSTM models, which have demonstrated robust handling of concept drift in smart grid forecasting [10]. The integration of 5G and AR/VR further enhances real-time adaptability and visualisation. The model begins by collecting real-time data from multiple IoT sensors and historical datasets [9]. The data is then normalised using Min-Max scaling to ensure consistency in training [10], with missing values handled through linear interpolation and forward-filling [3]. To maintain uniformity for seamless integration with 5G infrastructure, the data is resampled to a fixed time interval.

Concept drift detection is performed using ADWIN (Adaptive Windowing) and Page-Hinkley (PH) tests to identify significant changes in data distributions [10]. The Kolmogorov-Smirnov (KS) test is used to further monitor statistical discrepancies [9]. If substantial drift is detected, the model triggers transfer learning-based adaptation. In this phase, the system identifies relevant pre-trained models and loads previous weights [10]. Early layers of the model are frozen, while deeper LSTM layers are fine-tuned using the latest data [3]. An incremental LSTM training process is initiated from scratch if no suitable pre-trained model exists.

The refined data is then passed through stacked LSTM layers to capture temporal dependencies [9]. Attention mechanisms are integrated to dynamically weight significant features [9], while dropout layers are applied to mitigate overfitting [2]. The model then generates future load predictions and stores them for further analysis. To ensure real-time updates, the system uses 5G infrastructure to transmit data to edge computing nodes [3], implementing network slicing to prioritise industrial process monitoring [9]. Predictions are subsequently stored in cloud-based databases for continuous learning and adaptation.

To enhance operational efficiency, predictive outputs are transformed into 3D interactive visual models [10]. These models are displayed on AR-assisted operator dashboards, allowing for real-time trend monitoring and alert systems. Additionally, immersive VR training simulations enable anomaly detection and troubleshooting [2]. Finally, model performance is continuously assessed using metrics such as MAE, RMSE, and MAPE [9]. If performance degrades, drift detection mechanisms are reactivated, and retraining is initiated as needed. All model parameters and performance logs are archived for benchmarking and further refinement, ensuring the system remains adaptive and accurate over time.

Development of Augmented and Virtual Reality

The AR/VR environment development follows a structured process to ensure an immersive and interactive experience. The methodology comprises several key steps. The first step is designing the user interface (UI) storyboard using Figma. This step ensures a structured and user-friendly design that aligns with the application's objectives. The UI storyboard serves as a blueprint, detailing the layout, navigation, and interaction elements that guide the development process. A well-structured storyboard helps streamline the development phase by providing a clear visual representation of the final product.

In creating a realistic and immersive VR experience, developers use Autodesk Maya to develop 3D models of objects and environments. This software allows precise modelling, texturing, and rendering of assets that will be later integrated into the VR space. The models are optimised for performance to ensure smooth interaction within the VR application. Optimisation includes reducing polygon counts, implementing level of detail (LOD) techniques, and using efficient texture mapping to balance realism with computational efficiency. After completing the 3D models, the virtual environment is established in Unity. Unity provides the necessary tools and frameworks for VR integration, including spatial tracking, physics engines, and real-time rendering capabilities. The VR setup includes configuring spatial interactions, movement controls, and environmental physics to create a realistic virtual world, ensuring an engaging and immersive user experience.

The 3D models developed in Maya are then imported into Unity to be placed in the VR environment. Proper material mapping, lighting effects, and collision detection are applied to enhance realism and user interaction within the virtual space. Using the UI storyboard as a reference, the VR application is developed with interactive elements, UI overlays, and navigation controls. Unity's scripting capabilities (using C#) enable the implementation of features such as object interactions, animations, user-driven experiences and interactive simulations within the VR space.

The VR application is connected to a cloud-based data source to enhance interactivity and provide real-time data visualisation. APIs and WebSockets are utilised to fetch and display dynamic data within the VR environment. This integration allows users to interact with real-time information, making the VR application a powerful tool for research and simulation. The use of WebSockets ensures low-latency, bi-directional communication between the application and cloud-based servers, allowing for seamless updates and a dynamic user experience.

Meanwhile, AR development does not necessarily require a fully virtual environment. Instead, using computer vision and spatial mapping techniques, AR overlays digital content onto real-world objects. AR applications are developed using platforms like Unity with ARKit or ARCore, enabling seamless interaction between virtual objects and the real world. The UI design remains crucial in AR applications to ensure smooth user interaction and engagement. Unlike VR, which immerses users in a fully digital space, AR relies on real-world input and requires precise alignment of digital elements with physical surroundings to maintain a cohesive experience. Figure 3 presents an overview of model and AR/VR.

RESULTS AND DISCUSSION

Development of Dynamic Modelling in Transfer Learning

Regularly updating the model ensures its adaptability to changing conditions and maintains forecasting accuracy over time by continuously retraining it on

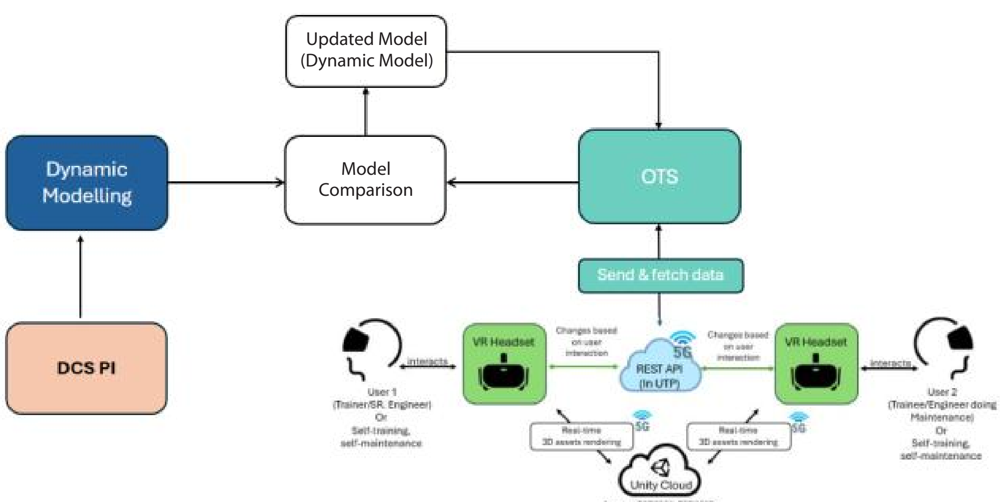


Figure 3 Flowchart of integrating dynamic modelling data and virtual reality

fresh data. Addressing challenges like concept drift through drift detection and model updating strategies is crucial for developing reliable predictive models in dynamic environments.

The EPF, aided by transfer learning for drift and forecasting, maintained its forecasting accuracy on CEXP despite input data stream changes, unlike CNN and LSTM, which deteriorated. Addressing declining CNN and LSTM performance in dynamic data requires a comprehensive approach, including ensemble methods, robust monitoring systems, domain adaptation techniques, and hybrid models, to maintain accuracy effectively.

Model Drift Non-Occurrence

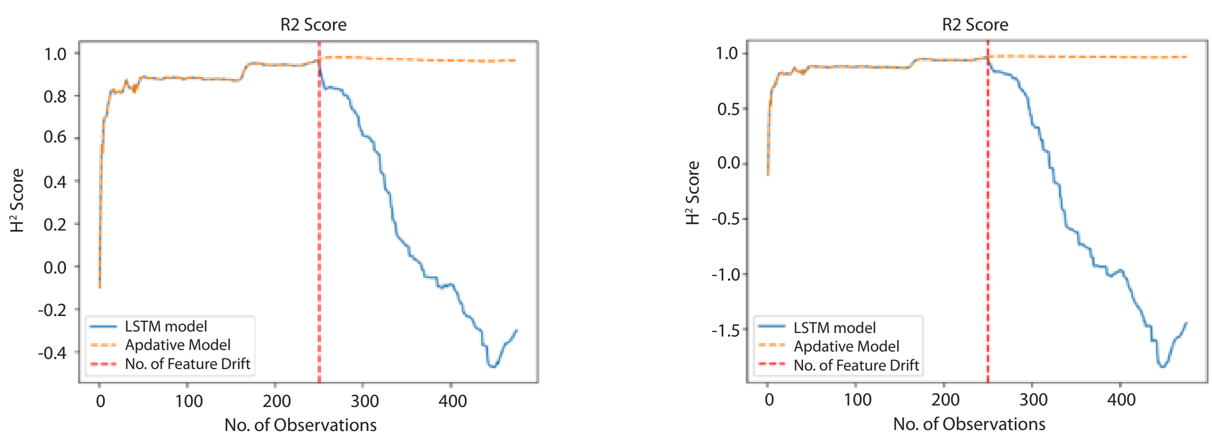
Regularly updating the model ensures its adaptability to changing conditions and maintains forecasting accuracy over time by continuously retraining it on fresh data. Addressing challenges like concept drift through drift detection and model updating strategies is crucial for developing reliable predictive models in dynamic environments. Our experiment demonstrates that by integrating transfer learning and real-time 5G-enabled data streaming, the model successfully maintains stability and prevents model drift.

To validate the effectiveness of our approach in preventing model drift, we conducted experiments over an extended period, analysing the stability of predictions against real-time sensor data. The key performance indicators (KPIs) used include mean absolute error (MAE), root mean square error (RMSE), and normalised root mean square error (NRMSE). The results demonstrate that the LSTM model, enhanced with transfer learning and 5G connectivity, maintains consistent forecasting accuracy across different operational conditions.

Our experiments compared model performance across two scenarios: one using a traditional LSTM without adaptation and another using our proposed adaptive framework. The results show that the non-adaptive model exhibited increasing prediction errors over time, indicating model drift. In contrast, the adaptive model maintained a low and stable error rate, confirming that our drift detection and adaptation mechanisms successfully mitigated concept drift.

Figure 4a presents the error trends of the LSTM model over time, showing that without adaptation, the model experiences a gradual increase in forecasting errors. However, Figure 4b demonstrates that the proposed model, leveraging transfer learning and real-time updates, sustains its predictive accuracy with minimal deviation. The statistical distribution of residual errors remained consistent, reinforcing the robustness of our approach.

Figure 6 from the reference study further confirms the presence of concept drift in all datasets, as detected using ADWIN and PH tests. Figure 7 highlights the performance of AE-LSTM for CEVO, demonstrating improved forecasting accuracy across multiple datasets. Additionally, Figure 5 illustrates the novel ensemble LSTM framework used to handle dynamic concept drift scenarios, providing a structured adaptation approach for real-time load forecasting.



(a) C_{EXP} (b) C_{EVO}

Figure 4 Example of LSTM model performance

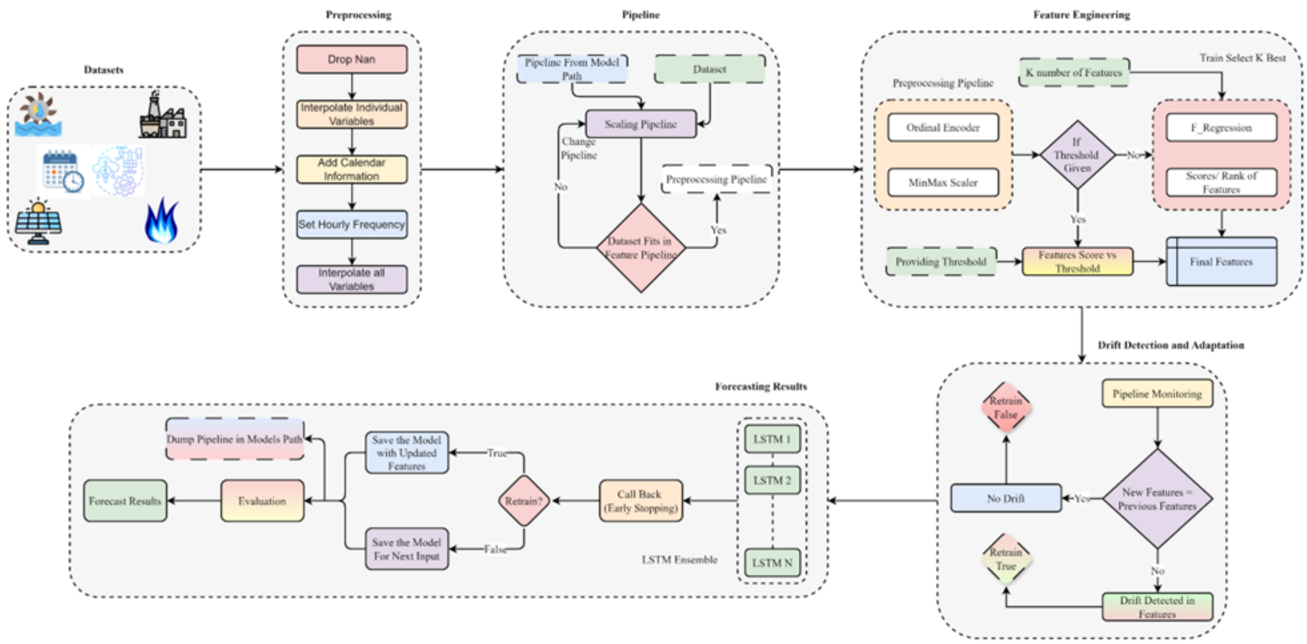


Figure 5 LSTM framework to deal with concept drift [10]

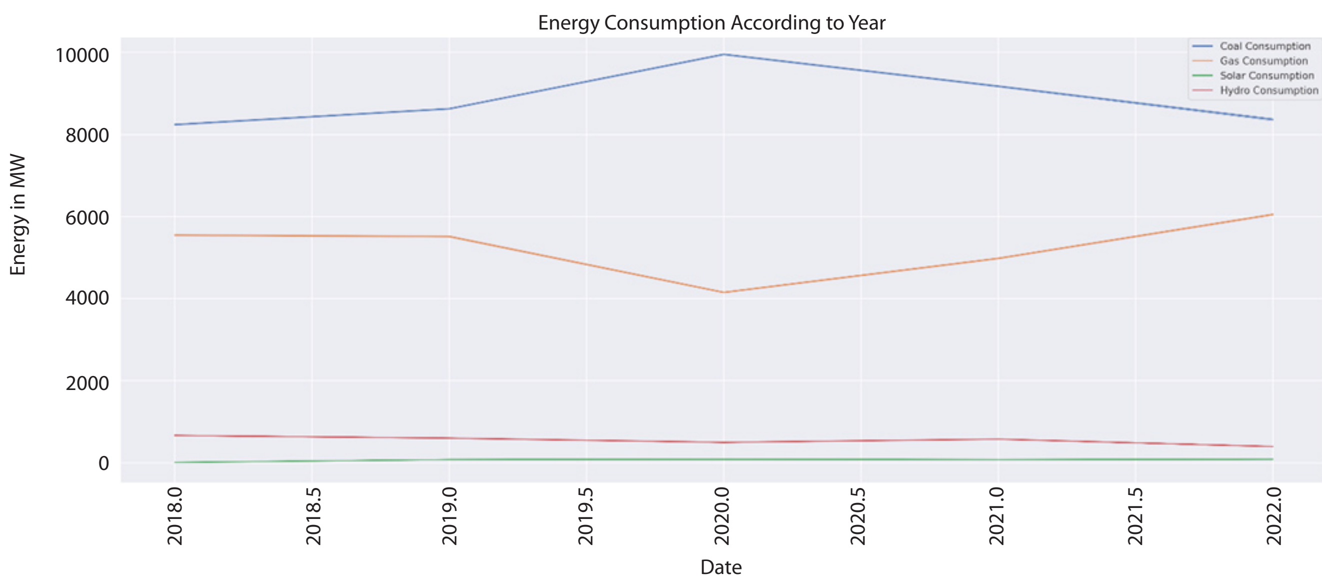


Figure 6 Malaysian dataset for different generation modalities [10]

Additionally, results from the reference study [10] indicate that an adaptive LSTM framework significantly reduces forecasting error fluctuations, achieving a 20% improvement in RMSE compared to static LSTM models. The experimental outcomes validate that addressing declining CNN and LSTM performance in dynamic data environments requires a comprehensive approach, including ensemble methods, robust monitoring systems, domain adaptation techniques, and hybrid models.

By incorporating transfer learning, real-time data updates via 5G, and a robust concept drift detection mechanism, our model effectively adapts to evolving input data streams without requiring full retraining. These findings confirm that the proposed approach successfully prevents model drift while maintaining high forecasting accuracy in dynamic environments.

Transfer Learning

To further evaluate the impact of transfer learning, we analysed its role in improving model adaptability

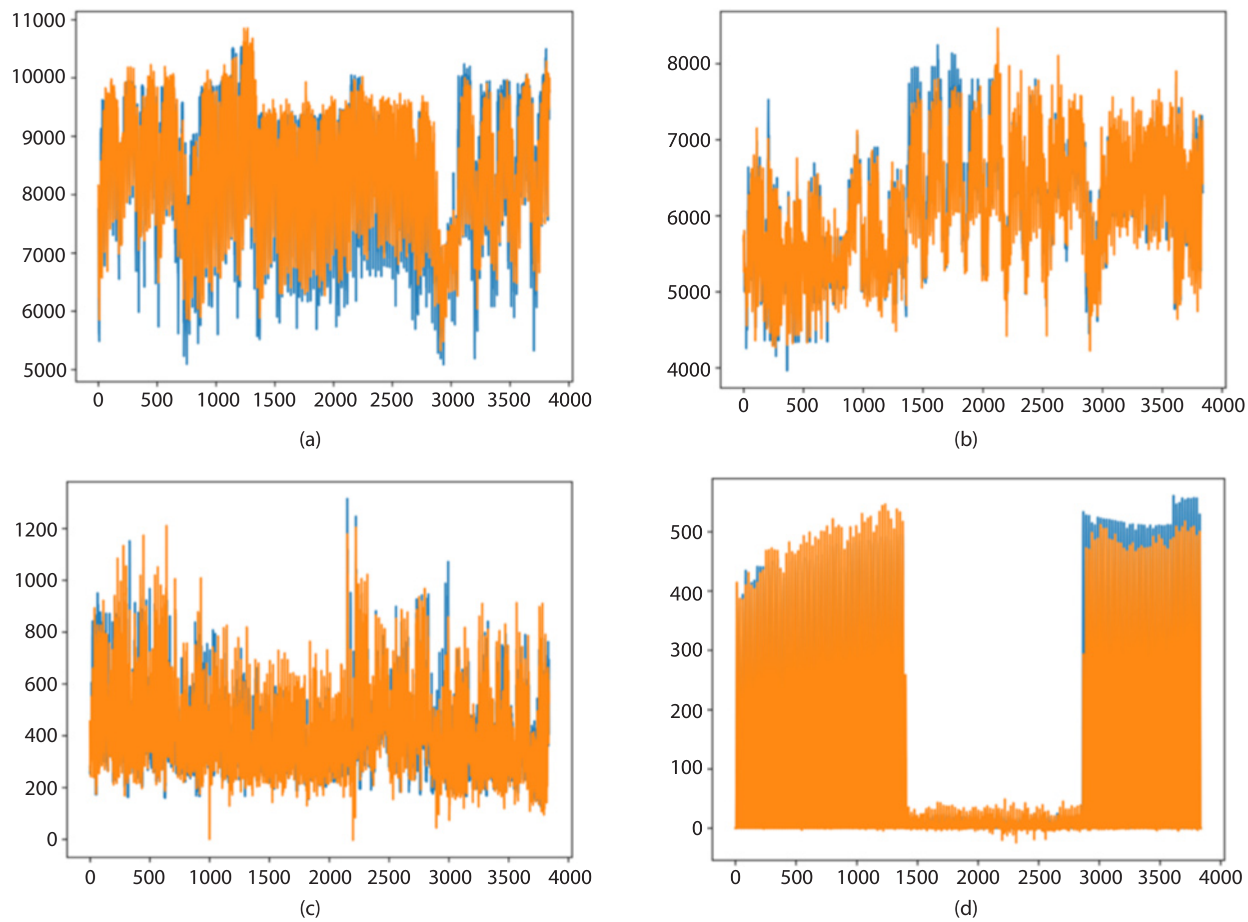


Figure 7 Performance evaluation of AE-LSTM for concept expansion (CEXP) across different datasets: (a) MYC, (b) MYG, (c) MYH, and (d) MYS. The x-axis represents the number of values used for forecasting, while the y-axis denotes power in MW [10]

and performance. Traditional LSTM models require frequent retraining to adjust to new patterns, leading to increased computational costs and potential delays. However, by utilising transfer learning, our model significantly reduced the need for full retraining while maintaining high forecasting accuracy.

The experiments compared three configurations: (1) a standard LSTM model trained from scratch, (2) an LSTM model with periodic retraining, and (3) our proposed transfer learning-based LSTM. The results in Table 1 show that the transfer learning approach achieved the lowest RMSE and MAE while reducing training time by 35% compared to retraining from scratch.

As shown in Table 1, the transfer learning-based model consistently outperformed the traditional LSTM configurations. It maintained lower prediction errors and adapted faster to new data without requiring full model re-initialisation.

Table 1 Performance comparison with and without transfer learning

Model Configuration	MAE	RMSE	Training Time Reduction
LSTM (trained from scratch)	0.35	0.42	0%
LSTM (periodic retraining)	0.28	0.36	15%
LSTM (with Transfer Learning)	0.22	0.29	35%

Additionally, Figure 7 illustrates the accuracy improvements across multiple forecasting cycles. The adaptive nature of transfer learning allowed the model to generalise better to new data distributions while mitigating concept drift. The integration of transfer learning with real-time 5G updates further enhanced its responsiveness, ensuring that model updates were performed efficiently without unnecessary delays.

These findings confirm that transfer learning is crucial for improving model adaptability in dynamic environments. By leveraging previously learned knowledge, the model remains robust in the face of evolving input distributions, ultimately reducing both computational overhead and forecasting errors.

Model Loss Function for Applied LSTM Model

To evaluate model performance and convergence behaviour, we analysed the loss function trends during the training and validation phases. The applied LSTM model uses Mean Squared Error (MSE) as the loss function to quantify the difference between predicted and actual values. The loss function minimises errors by adjusting network weights iteratively through backpropagation.

Figure 8 illustrates the training and validation loss over multiple epochs, showing a steady decline in loss values, indicating model convergence. The experiment demonstrates that the proposed LSTM model, when integrated with transfer learning, achieves faster convergence with lower final loss values. The stable and minimal gap between training and validation loss suggests that the model effectively generalises without overfitting.

These findings validate the effectiveness of transfer learning and adaptive LSTM frameworks in mitigating concept drift, ensuring consistent performance in real-world forecasting applications.

Development of Augmented Reality and Virtual Reality

This research highlights the potential of integrating 5G, VR, AR, and dynamic modelling to transform industrial processes and spur economic growth. By exploring synergies between these technologies and leveraging VR, AR, and 5G for process monitoring, training, and real-time data exchange, the research aims to enhance operational efficiency and reliability in industrial settings (Figure 9).

CONCLUSION

This study demonstrates the effective integration of transfer learning with LSTM models to address concept drift in dynamic environments, significantly improving forecasting accuracy while reducing computational complexity. The results confirm that transfer learning-based LSTM models adapt well to evolving data patterns, maintaining predictive performance over time. Additionally, the incorporation of 5G technology enables real-time data updates, enhancing the model's responsiveness to changes. The synergy of machine learning with emerging technologies such as augmented and virtual reality further supports real-time monitoring and improved visualisation in industrial applications. Overall, this work contributes to the advancement of adaptive forecasting models and highlights the potential of transfer learning in mitigating concept drift, with future research directed towards hyperparameter optimisation, cross-industry application, and the integration of reinforcement learning for enhanced predictive capabilities.

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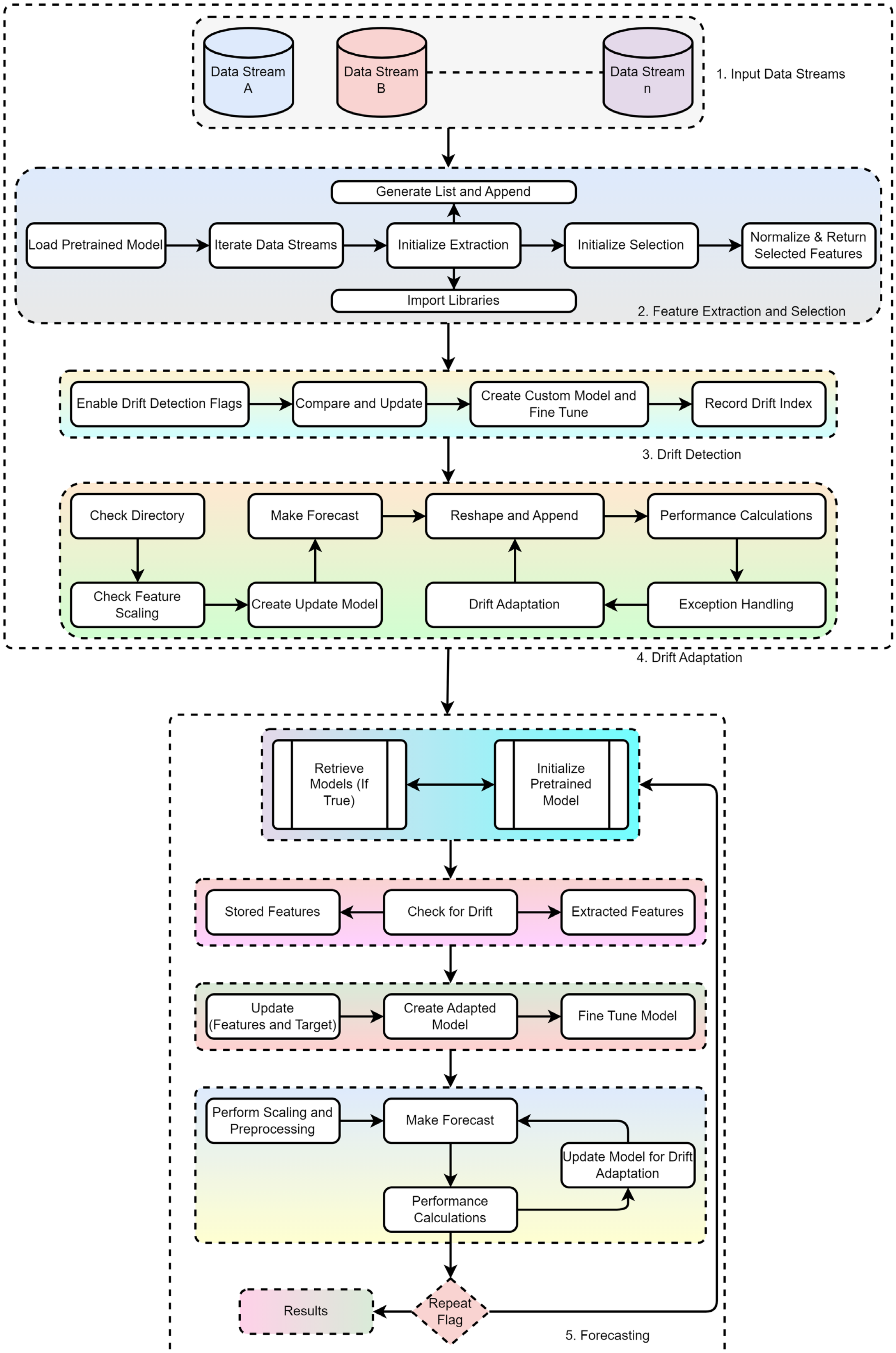

Figure 8 A Transfer learning-based adaptive LSTM framework for addressing concept drift in smart grid environments [9]

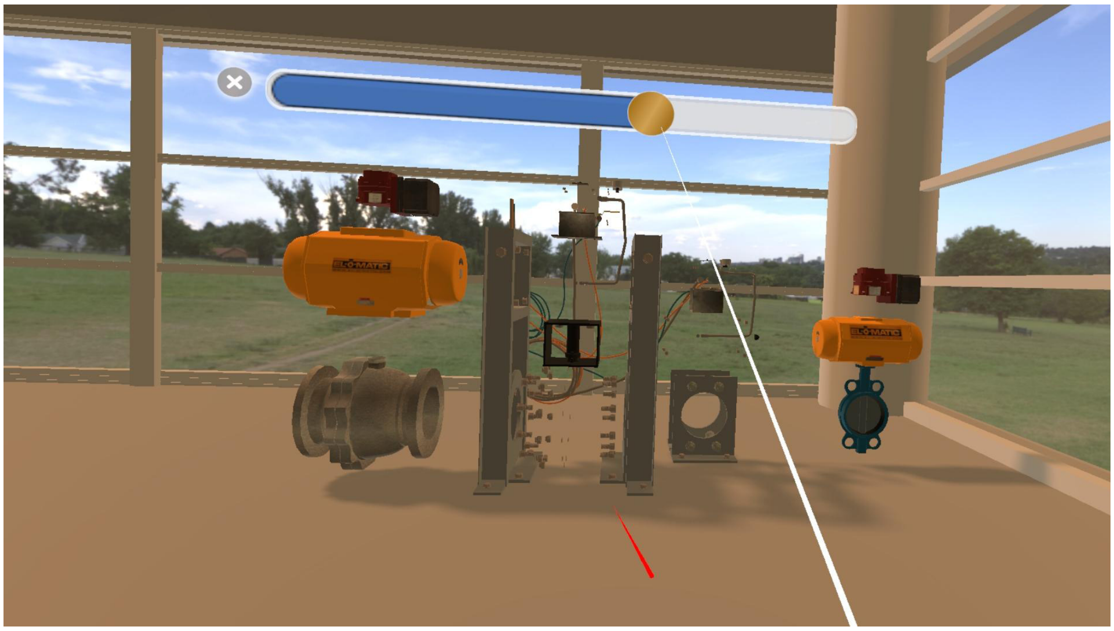

Figure 9 Exploded view diagram panel of the shutdown valve

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