



**OPTIMAL SHORT TERM LOAD FORECASTING USING LSSVM
AND IMPROVED BFOA CONSIDERING MALAYSIA PANDEMIC
DISRUPTED SITUATION**



MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

2024



Faculty of Electrical Engineering and Technology

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Farah Anishah binti Zaini

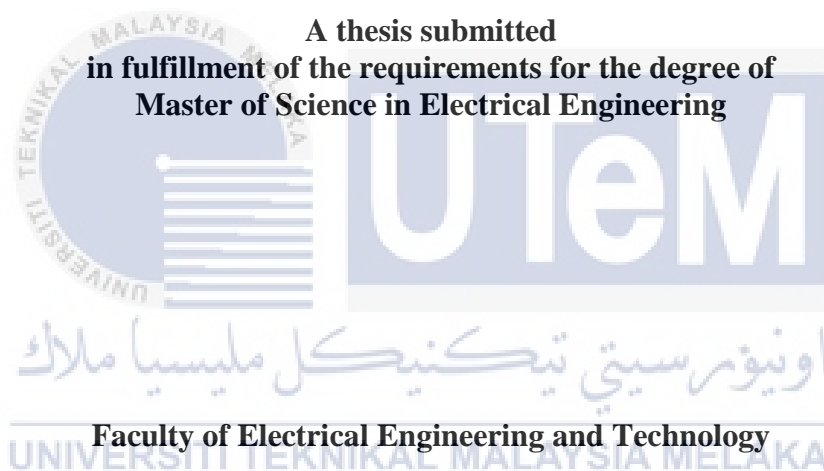


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FARAH ANISHAH BINTI ZAINI



UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

DEDICATION

To my beloved mother and father.



ABSTRACT

The COVID-19 pandemic's unprecedented disruptions significantly impacted electricity demand patterns across the globe. In Peninsular Malaysia, strict lockdown measures (Movement Control Orders - MCOs) led to the closure of non-essential businesses and stay-at-home orders. These sudden and dramatic shifts in consumption patterns posed a significant challenge for power system operations, which rely heavily on accurate short-term load forecasting (STLF) for efficient and cost-effective operation. Inaccurate forecasts can have substantial economic consequences, especially during peak load periods. Due to that reason, in this study, the hybrid forecasting model based on the Least Square Support Vector Machine (LSSVM) and Improved Bacterial Foraging Optimization Algorithm (IBFOA) is developed to perform an accurate STLF and applied to load in Peninsular Malaysia during the pandemic disrupted situation. The IBFOA is proposed by modifying the chemotaxis process in BFOA using a Sine Cosine Algorithm (SCA), which improves the convergence speed and accuracy of the algorithm. The LSSVM-IBFOA model demonstrates superior performance compared to standalone LSSVM and LSSVM-BFOA based on Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Normalized RMSE (NRMSE), and Determination Coefficient (R^2). Using the proposed hybrid method, LSSVM-IBFOA consistently achieves the most significant error reductions for each errors value based on the average of five day-types (Monday-Sunday), on the testing datasets for the years 2020 and 2021. Furthermore, the proposed method demonstrates superior generalizability, with a substantial decrease in testing error compared to validation error in both years. For instance, in 2020, MAPE, MAE, MSE, RMSE, and NRMSE all witnessed reductions of 33.02%, 32.15%, 59.39%, 33.11%, and 32.75%, respectively. Similar trends were observed in 2021. This suggests the model's ability to adapt to changing load patterns, making it a valuable tool for real-world forecasting applications. Improved forecasting accuracy empowers energy providers to optimise resource allocation, power generation scheduling, and grid management, leading to potential cost reductions and increased efficiency.

**RAMALAN BEBAN JANGKA PENDEK OPTIMAL MENGGUNAKAN LSSVM DAN
BFOA YANG DITAMBAHBAIK MENGAMBIL KIRA SITUASI PANDEMIK DI
MALAYSIA YANG TERUK**

ABSTRAK

Gangguan wabak COVID-19 yang belum pernah berlaku sebelum ini memberi kesan ketara kepada corak permintaan elektrik di seluruh dunia. Di Semenanjung Malaysia, langkah penutupan yang ketat (Perintah Kawalan Pergerakan - PKP) menyebabkan penutupan perniagaan yang tidak penting dan perintah tinggal di rumah. Peralihan mendadak dan dramatik dalam corak penggunaan ini menimbulkan cabaran besar untuk operasi sistem kuasa, yang sangat bergantung pada ramalan beban jangka pendek (STLF) yang tepat untuk operasi yang cekap dan kos efektif. Ramalan yang tidak tepat, terutamanya semasa tempoh beban puncak, boleh membawa kesan ekonomi yang besar. Atas sebab itu, dalam kajian ini, model ramalan hibrid berdasarkan Mesin Vektor Sokongan Kuasa Dua Terkecil (LSSVM) dan Algoritma Pengoptimuman Makanan Bakteria (IBFOA) yang ditambahbaik dibangunkan untuk melaksanakan STLF yang tepat dan digunakan di Semenanjung Malaysia semasa keadaan terganggu pandemik. IBFOA dicadangkan dengan mengubah suai proses chemotaxis dalam BFOA menggunakan Algoritma Kosinus Sinus (SCA), yang meningkatkan kelajuan penumpuan dan ketepatan algoritma. Model LSSVM-IBFOA menunjukkan prestasi unggul berbanding LSSVM dan LSSVM-BFOA sendiri berdasarkan Ralat Peratusan Mutlak Min (MAPE), Ralat Purata Purata (MAE), Ralat Purata Kuasa Akar (RMSE), Ralat Purata Kuasa Purata (MSE), RMSE Ternormal (NRMSE), dan Pekali Penentuan (R^2). Dengan menggunakan kaedah hibrid yang dicadangkan, LSSVM-IBFOA secara konsisten mencapai pengurangan ralat yang paling ketara berdasarkan purata lima jenis hari (Isnin-Ahad), pada set data ujian untuk tahun 2020 dan 2021. Selain itu, ia mempamerkan unggul boleh digeneralisasikan, dengan pengurangan ketara dalam ralat ujian berbanding ralat pengesahan untuk kedua-dua tahun. Contohnya, pada tahun 2020, MAPE, MAE, MSE, RMS dan NRMSE semua menyaksikan pengurangan masing-masing sebanyak 33.02%, 32.15%, 59.39%, 33.11%, dan 32.75%. Trend yang sama diperhatikan pada tahun 2021. Ini menunjukkan keupayaan model untuk menyesuaikan diri dengan mengubah corak beban, menjadikannya alat yang berharga untuk aplikasi ramalan dunia sebenar. Ketepatan ramalan yang lebih baik memperkasakan penyedia tenaga untuk mengoptimumkan peruntukan sumber, penjadualan penjanaan kuasa dan pengurusan grid, yang membawa kepada pengurangan kos yang berpotensi dan peningkatan kecekapan.

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LIST OF ABBREVIATIONS

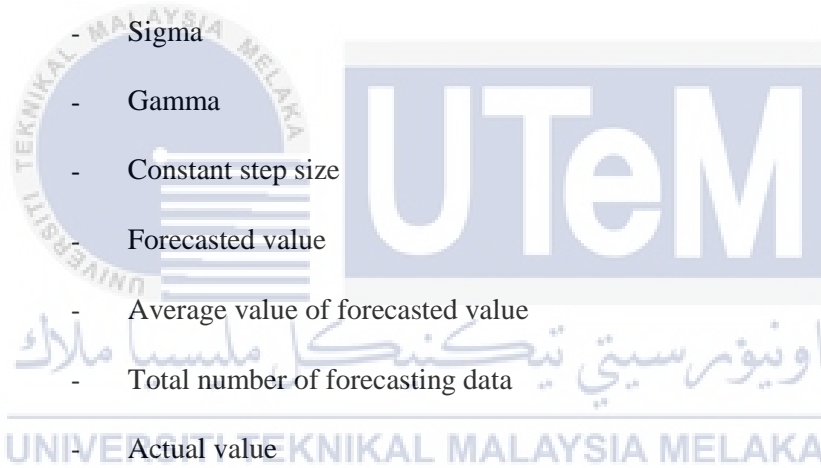
<i>ANN</i>	-	Artificial neural network
<i>ARIMA</i>	-	Autoregressive Integrated Moving Average
<i>ARMA</i>	-	Autoregressive moving average
<i>BFOA</i>	-	Bacterial foraging optimization algorithm
<i>BPNN</i>	-	Back propagation neural network
<i>COVID – 19</i>	-	Coronavirus disease
<i>DL</i>	-	Deep learning
<i>EE</i>	-	Energy efficiency
<i>GDP</i>	-	Gross domestic product
<i>IBFOA</i>	-	Improved bacterial foraging optimization algorithm
<i>KF</i>	-	Kernel function
<i>LF</i>	-	Load forecasting
<i>LSSVM</i>	-	Least Square Support Vector Machine
<i>LSTM</i>	-	Long Short-Term Memory
<i>LTLF</i>	-	Long-term load forecasting
<i>MAE</i>	-	Mean absolute error
<i>MAPE</i>	-	Mean absolute percentage error
<i>MCO</i>	-	Movement control order
<i>ML</i>	-	Machine learning
<i>MSE</i>	-	Mean square error
<i>MTLF</i>	-	Medium-term load forecasting
<i>NETR</i>	-	National energy transition roadmap
<i>NRMSE</i>	-	Normalized Root mean square error

<i>PCC</i>	-	Pearson correlation method
R^2	-	Determination Coefficient
<i>RBF</i>	-	Radial Basis Function
<i>RE</i>	-	Renewable energy
<i>RMSE</i>	-	Root mean square error
<i>STLF</i>	-	Short-term load forecasting
<i>SVM</i>	-	Support vector machine
<i>SVR</i>	-	Support vector regression
<i>TCN</i>	-	Temporal convolutional network
<i>TNB</i>	-	Tenaga Nasional Berhad



LIST OF SYMBOLS

$\sum xy$	-	Sum of the products of paired scores
$\sum x^2$	-	Sum of squared X scores
$\sum y^2$	-	Sum of squared Y scores
x_{max}	-	Maximum boundaries of the attribute values
x_{min}	-	Minimum boundaries of the attribute values
$\varphi(x)$	-	Non-linear mapping function
σ	-	Sigma
γ	-	Gamma
$C(i)$	-	Constant step size
\widehat{w}_i	-	Forecasted value
\bar{x}	-	Average value of forecasted value
p	-	Total number of forecasting data
w_i	-	Actual value
a	-	Constant in SCA



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LIST OF PUBLICATIONS

The following are the list of publications related to the work of this thesis:

Zaini, F. A., Intan Azmira, W. A. R., Sulaima, M. F., Kim, G. C., and Hassan, E. E. 2024. Bacterial Foraging Optimization Based Least Square Support Vector Machine for Short-Term Electricity Load Forecasting. *International Conference on Green Energy, Computing and Sustainable Technology (GECOST 2024)*, pp. 121–126.

Zaini, F. A., Sulaima, M. F., Razak, I. A. W. A., Zulkafli, N. I., and Mokhlis, H. 2023. A Review on the Applications of PSO-Based Algorithm in Demand Side Management: Challenges and Opportunities. *IEEE Access*, pp. 53373–53400.



CHAPTER 1

INTRODUCTION

1.1 Background

Energy serves as a fundamental driver of economic expansion and development of the countries. The secondary source of energy which is electricity is an essential commodity delivered to end users through several stages such as production, transmission, and planning (Kök et al., 2022). Electricity demand is driven by many factors and changes according to the weather, local demographics and special events or seasons. The outbreak of coronavirus disease (COVID-19) has significant impact on energy demand and daily consumption patterns in Malaysia due to the enforcement of various phases of Movement Control Order (MCO). The energy demand in Malaysia has correlated with gross domestic product (GDP) growth as the economy depends on energy-intensive industries such as manufacturing and services. The lower GDP growth affected the demand due to the impact of the COVID-19 pandemic.

In 2020, the GDP dropped by 5.54%, consequently, the electricity generation decreased by 2.4% and the total final energy consumption experienced a downtrend trend at -0.5% especially in the industry sector compared to 2019. Figure 1.1 illustrates the final electricity consumption (ktoe) by major sectors in Malaysia over seven years. Notably, the industrial sector experienced a decline of 5.11% in 2020 compared to 2019, which was counterbalanced by a 13.09% increase in the residential sector. Overall, the final electricity consumption in 2020 decreased by 4.00% compared to 2019, reaching a total of 13,007 ktoe.

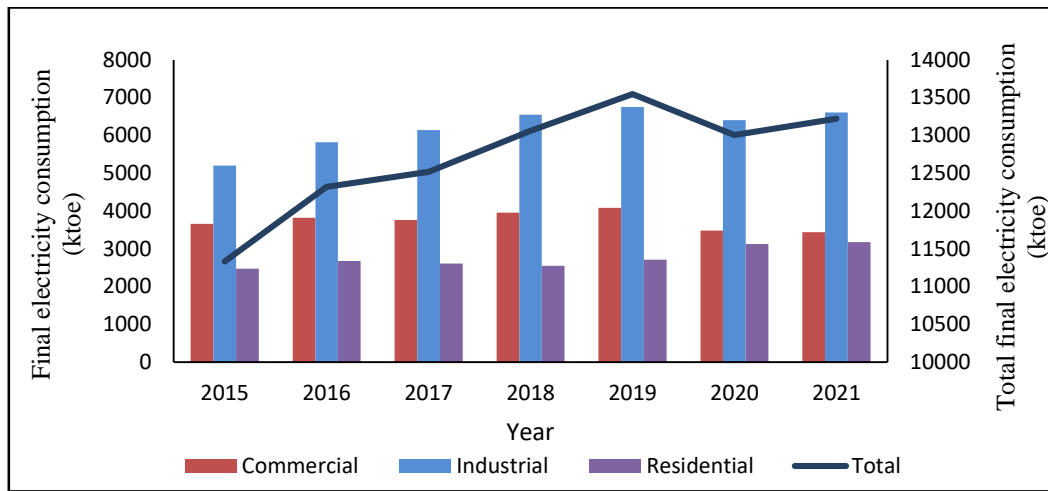


Figure 1.1 The final electricity consumption in Malaysia

Therefore, the government has planned an economic recovery program to stimulate the economy, with an expected GDP growth of 3.44% per year from 2020 until 2030 (Zulkifli, 2021). This program aligns with the National Energy Transition Roadmap (NETR), which aims to leverage energy transition as a tool for economic restructuring, fostering green growth, and enhancing key metrics such as GDP, job creation, and citizen/business well-being. Successful implementation of the NETR is projected to generate significant economic benefits, including an 86.67% increase in GDP by 2023 and the creation of 310,000 jobs by 2050. This anticipated economic growth highlights the growing energy demand.

To meet this demand while achieving its sustainability goals, Malaysia's energy landscape is projected for a significant transformation, balancing energy demand growth with a resolute transition towards renewable energy (RE) and energy efficiency (EE). The NETR identifies RE and EE as key levers within its six energy transition, aiming to promote economic opportunities, reduce emissions, ensure cost-effectiveness, and foster social inclusivity (Ministry of Economy, 2023).

The Planned Energy Scenario (PES) forecasts a 2.0% annual increase in overall energy demand; however, strategic integration of RE and EE measures is expected to curb final energy consumption by 15-22%. The electricity utility in Peninsular Malaysia has set an ambitious target of achieving 20% RE capacity and attaining net-zero emissions by 2050. This goal will be pursued through a sustainable pathway that aims to reduce emission intensity by 35% and halve coal generation capacity by 2035 (IRENA, 2023). The exponential growth and innovation in RE are actively shaping a more interconnected and environmentally sustainable global energy future.

Accurate electricity forecasting serves a pivotal role in accelerating this transition, offering precise insights into future energy demand and facilitating optimized generation strategies that minimize environmental impact and maximize sustainability (Aswanuwath et al., 2023). Electricity load forecasting is the fundamental aspect of ensuring the stable operation of the power system (Shoujiang Li et al., 2023). Load forecasting assists electrical power utilities in making important decisions, minimizing the costs of power production and increasing the accuracy of electrical power facilities (Jahan et al., 2020). The electricity demand is forecasted in advance as very short-term, short-term, medium-term and long-term (Mir et al., 2020).

Among the horizons, short-term load forecasting (STLF) is taking centre stage in the realm of electricity load forecasting, as evidenced by the surge in research efforts by researchers (Petropoulos et al., 2022). Moreover, STLF helps power system operators with various decision-making in the power system including supply planning, generation reserve and demand-side management (Fallah et al., 2019). By enabling proactive planning and adjustments based on forecasted short-term demand fluctuations, STLF ultimately safeguards grid stability and ensures the continuous, reliable delivery of electricity to consumers.

Tenaga Nasional Berhad (TNB), the largest electricity utility company in Malaysia, manages the core activities in power systems such as generation, transmission, and distribution. The transmission division manages all aspects of transmission, from planning and evaluating future needs to implementing and maintaining infrastructure. Load forecasting, a crucial element of power system planning, enables TNB to predict and meet electricity demand effectively (Abd. Razak et al., 2009).

TNB performs three types of forecasting: short-term, medium-term and long-term for its power operation and development purposes. TNB's forecasting method demonstrated a significant shift in the early 1980s, transitioning from simple judgmental approaches to incorporating data-driven methods like time series and regression analysis. This evolution continued with the inclusion of income elasticity, sectoral trends, and end-use techniques, leading to a more multifaceted and robust forecasting approach (Hock-Eam and Chee-Yin, 2016).

Accurate STLF models have consistently contributed to improved revenue and efficiency for electricity distribution and generation companies. However, achieving high forecasting accuracy remains a crucial challenge due to the inherent complexities of load data. This data exhibits both static (long-term trends) and dynamic (short-term fluctuations) characteristics, posing difficulties for traditional approaches that rely on singular models or the integration of individual methods (Ahmad et al., 2022). Particularly, during the disrupted situations, the demand pattern has fluctuated significantly. The unprecedented shifts in human behaviour triggered by the COVID-19 pandemic, particularly related to power usage, presented significant challenges for STLF.

Existing forecasting methods, which were not designed to anticipate such dramatic and sudden changes in consumption patterns, struggled to maintain accuracy (Aswanuwath et al., 2023). Accurate STLF is essential for ensuring the cost-effectiveness and reliability

of power system operations (Chen et al., 2020). Inaccurate forecasts, particularly concerning peak load periods, can lead to significant economic consequences due to unexpected power generation requirements and surplus production (Lee and Cho, 2022). Over the years, researchers have developed numerous state-of-the-art methods specifically tailored to address STLF problems. These methods highlight the superiority of non-linear models in capturing the complex and dynamic behaviour of load time series data. Consequently, non-linear machine learning (ML) methods, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), have garnered significant attention in the literature due to their effectiveness in this domain (Morais et al., 2023).

Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are widely employed error measures to evaluate the accuracy of forecasting models. Both metrics are expressed as percentages, with lower values indicating greater forecasting accuracy (Mansouri et al., 2023). Studies have shown that a 1% reduction in MAPE can translate to significant cost savings on the production side, ranging from 0.1% to 0.3% reduction in generation costs (Gao et al., 2019). Thus, the primary objective of load forecasting is to ensure a secure and reliable electricity supply while simultaneously minimizing operational costs and energy waste.

Additionally, this study contributes to multiple Sustainable Development Goals (SDGs) by the United Nations including Affordable and Clean Energy (SDG 7), Industry, Innovation and Infrastructure (SDG 9), Responsible Consumption and Production (SDG 12) and Climate Action (SDG 13) by providing electricity forecasting insights and valuable guidance in various situations to decision makers. This approach facilitates accurate forecasting thus, optimized resource allocation (SDG 7), minimises energy waste (SDG 12), mitigates environmental impact (SDG 13), reduces financial losses, promotes sustainable infrastructure and clean technologies (SDG 9), and ultimately fosters sustainable economic