Load Modeling for Cryptocurrency Mining Devices Using System Identification and Machine Learning

Ghali Ahmad[1], Md Shafiullah[1,2,4], Nezar M. AL-Yazidi[1,3], Mohamed Zaery[2], Mujahed Al-Dhaifallah[1,2], M. A. Abido[2,4,5,6], and Faris Aljehani[7]

[1]Control & Instrumentation Engineering Department, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia
[2]IRC for Sustainable Energy Systems, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia
[3]IRC for Smart Mobility and Logistics, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia
[4]K.A.CARE Energy Research & Innovation Center, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia
[5]Electrical Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
[6]SDAIA-KFUPM Joint Research Center for Artificial Intelligence, King Fahd University of Petroleum & Minerals, 31261, Saudi Arabia
[7]Dema Energy, Dhahran 31261, Saudi Arabia

{g202214940, shafiullah, nalyazid, mohamed.mohamedali, mujahed, mabido}@kfupm.edu.sa, faris@dema-holding.com

***Abstract*—This paper presents a novel flexible load model tailored for cryptocurrency mining applications, specifically designed to dynamically adjust Application Specific Integrated Circuits-based mining operations based on real-time power availability. The model allows miners to use excess power during peak generation and reduce their usage during low power generation, all in support of maintaining a stable grid. The integration of the System Identification technique and some machine learning methods, such as Linear Regression, Support Vector Machine, and Neural Network Models, are used to identify and verify the proposed model against the genuine load data. Values of R^2 ranging from 0.9898 to 0.9953 point toward a very good agreement between the simulated and actual load profiles. The Neural Network Model presents the lowest RMSE, MSE, MAE, and WIE, which means that the model accurately captures the actual behavior of the load. This approach strengthens the efficiency and accuracy of mining processes and is quite compatible with renewable power generation and, therefore, the effective use of energy. This research forms the reference platform for adaptive load management for such intensive applications to provide a viable approach to renewable energy integration into high-power utilization systems.**

Index Terms — Cryptocurrency Mining, Application-Specific Integrated Circuits, Renewable Energy Sources, System Identification, Microgrid, Machine Learning.

ABBREVIATIONS

ASICs	: Application Specific Integrated Circuits
ESSs	: Energy Storage Systems
LR	: Linear Regrasion
NNM	: Neural Network
MAE	: Mean Absolute Error
MG	: Microgrid
ML	: Machine Learning
MSE	: Mean Square Error
RE	: Renewable Energy
RESs	: Renewable Energy Resources
RMSE	: Root Mean Square Error
R^2	: Coefficient of Determination
SCs	: Super Capacitors
S1	: System Identification
SVM	: Supported Vector Machine
WIA	: Willmott's Index of Agreement

I. INTRODUCTION

Cryptocurrency mining has been accepted as a vital component of blockchain networks, and its operation validates transactions and the network's safety using a highly complex mathematical computation [1]. In every mining environment, hash rate is the central concept, measuring the computational power used in solving application-specific cryptographic puzzles and accomplishing new blocks incorporated into the blockchain [1]. The core concept of a hash rate is examined by observing its impact on the mining process and its direct connection with power usage. Hash rate and power consumption have a direct relationship because an increase in the computation rate often results from higher power consumption [2]. Efficient cooling systems are essential for maintaining hardware functionalities and preserving its performance over time. A hash rate/power consumption ratio is the primary concern, as miners aim to maximize profits while at the same time minimizing operations costs. Optimization of this mining hardware means its ability to provide a higher hash rate and lower energy consumption, thus increasing profitability. Miners always explore ways to design new and more efficient mining equipment, such as Advanced Application Specific Integrated Circuits (ASICs) and Graphics Processing Units [3] However, electricity is one of the significant expenses that the miners incur, especially when the electricity price is high, and they may shift to another place to reduce the costs or switch to RESs if the electricity prices are too high. Miners assess the most profitable mining method by analyzing factors like hash rate, power consumption, cryptocurrency value, and mining difficulties in relation to cost. Profitability thus determines spending propensities and resource application in miners. By extension, miners across the globe can access and use the company's resources. Moreover, concerns are also being raised over the sustainability of cryptocurrency, especially given the steepest energy use in recent years [4].

Presently, renewable energy sources (RESs) such as hydro, wind, solar, nuclear, geothermal, and carbon generation with carbon offsets (as outlined in the Bitcoin Mining Council Q3 2021 Report) contribute to 57% of the energy consumption in cryptocurrency mining [5]. Renewable energy (RE) is gaining popularity, particularly among cryptocurrency miners who are motivated to lower their energy costs. RESs have become a cost-effective power option in many countries, offering a readily available and sustainable alternative to traditional energy sources. This is particularly true for nations promoting decarbonization through policy [6]. Additionally, crypto-mining operations may exhibit comparable utilization attributes with other data centers. However, their business model and output generate unique customer attributes. Crypto miners are among the most vulnerable business actors to energy price volatility since energy cost forms a significant portion of operational costs. They can also operate from various locations and frequently pursue agreements with utilities and power facilities to work on-site and circumvent grid costs. Miners can also work flexibly, as they are not restricted to a specific time of day and are rewarded in sprints rather than marathons, which eventually help regulate the short-term energy supply and demand [7]. These attributes offer three potential advantages to grid operators. The location of crypto mining devices near the energy source presents a distinctive opportunity to capitalize on underutilized generation capacity. Nuclear facilities in the United States use crypto mining to enhance their economics and increase sales to compete with lower-cost generation [7]. Crypto mining devices can help stabilize grid frequency, creating economic opportunities for solar projects in areas with excess power or interconnection delays. This additional revenue stream can support and accelerate the development of RE facilities [7].

A megatrend in the utility sector is the dynamic consumer involvement in the balance of short-term power supply and demand. Flexible loads are becoming increasingly crucial as the demand for electricity and the proportion of fluctuating RESs increase. In exchange for a discount or payment, recruiting customers willing to reduce their electricity consumption during specific times is frequently less expensive than implementing new supply resources to accommodate peak demand [8]. This demand response form is cost-effective for both the utility and its customers. Crypto mining has the potential to revolutionize demand response by allowing for the rapid reduction of large loads in exchange for a commission. It can also help achieve a seasonal balance in areas with high temperatures where electricity-consuming processes, such as desalination plants and air conditioning systems, produce seasonal loading profiles. Black Hills Energy and other innovative utilities are creating more adaptable tariffs for this emerging application. Additionally, crypto-mining devices can aid local utilities in the administration of distribution [8]. A utility can strategically position a mining operation that benefits the system most by utilizing crypto miners' locational flexibility. Absorbing excess power and facilitating the more reliable operation of a grid can also assist in balancing distributed generation.

Furthermore, Concerns about the environmental effects of using high energy by cryptocurrency mining have been kindled due to the significant energy usage connected with the process, especially in the Kingdom of Saudi Arabia, where energy from fossil sources dominates [9]. This paper emphasizes that mining operations leave a large carbon footprint, which has led to debates regarding implementing sustainable mining practices. Some miners or companies responsible for providing resources to the miners are exploring RESs such as solar, wind, or hydro to reduce reliance on fossil fuels and reduce CO_2 emission. RESs can be a long-term solution to energy consumption required by large-scale mining and against climate change. Hardware optimization, materialization of better cooling systems, and algorithms are among the methods used to optimize or improve energy efficiency in mining. These practices seek to reduce power consumption as much as possible while trying to keep hash rates on par with other mining competitors, making it more environmentally friendly [10].

A. *Related Work*

Numerous research studies have considered using different supplementary devices in microgrids (MGs) for load frequency control (LFC) in power systems with low inertia, including single and multi-microgrid configurations. Energy storage systems (ESSs) have been incorporated into MG to improve the dynamic response of the MG frequency by emulating conventional generation units. These studies have examined the supplementary devices integrated into the MG to support frequency regulations and minimize power wastage during a demanding period. The incorporation of ESSs has become essential in MGs, particularly those incorporating RESs, to support the synthetic inertia to enhance frequency behavior. In addition, electric vehicles (EVs) have been used as potential energy storage units, equipped with built-in battery storage systems capable of both charging and discharging energy to and from the power system. This approach reduces the need for additional ESSs [11]. On the other hand, supercapacitors (SCs) have recently been utilized as ESS, providing synthetic inertia with suitable rate of power injection and absorption [12]. Thus, the stored energy in SCs can effectively mitigate power imbalances, enhancing the frequency response of low-inertia power systems and reducing frequency deviations in the power system [13]. Furthermore, SCs provide various benefits, including an extended operational life, cost-effectiveness, rapid response times, and an exceedingly high power density. Subsequently, SCs and EVs provide synthetic inertia support for low-inertia MG power systems incorporating RESs through their bidirectional power functionality [14]. To improve the frequency response of an isolated MG, a virtual synchronous generator-based flywheel/battery ESS was implemented in [15]. At the same time, a hybrid flywheel/battery ESS has been employed in conjunction with EVs LFC [16]. Moreover, inverters with grid-forming or grid-following capabilities actively stabilize frequency in inverter-dominated setups, and demand response management systems contribute by adjusting loads to balance demand and supply [17]. Synchronous condensers add inertia and reactive power, providing frequency and voltage stability [18]. These devices maintain frequency stability, especially in low inertia.

TABLE I. REVIEW OF RELATED WORK

Ref.	***Flexible Loads***
[15]	Battery, Flysheel, and Electric Vehicle
[16]	Electric Vehicle and Battery
[13]	Super Capacitor and Battery
[12]	Super Capacitor and Electric Vehicle
[19]	Superconducting Magnetic Systems
[20]	Hydrogen Fuel Cell
[18]	Synchronous Machine
Proposed	**Proposed Flexible Load (ASIC) for Cryptocurrency Mining.**

B. *Main Contribution*

The related work, summarized in Table 1, showed that flexible loads, like ASICs, were not employed in any MG for mining cryptocurrency, stabilizing the system, and preventing power loss based on the author's knowledge.

The present research contribution is the novel modeling of flexible load (ASIC) that the miners will use for cryptocurrency mining. This innovative approach enables the load to harness surplus power during high-generation and reduce consumption during low-generation periods, thereby ensuring system stability.

II. LOAD MODELING

A. System Identification Toolbox Approach

System Identification (SI) is a technique for identifying an approximate mathematical model of dynamic systems using input-output data. An approximate mathematical model or model structure can be found to fit in a system using MATLAB's SI toolbox. The toolbox then allows the input of actual data to the experiment and the decision-making on what arithmetic operation to use in the algorithm. It also contains the routine for evaluating how effective the estimate system model is. It also uses several mathematical relations to forecast models based on the input-output data [21]. First, the data goes through pre-processing, where the data is either filtered or trends removed or normalized in case of unwanted noise or bias. The toolbox offers several model structures, such as transfer functions, state space models, and polynomial models. This means that through the analysis of the features of the system, the user can decide which model structure is most appropriate. The toolbox estimates the model parameters using the prediction error or subspace methods. This is done by reducing the difference between the real value produced by the model and the ideal value. When the desired model is completed, other forms of cross-validation accessible in the toolbox should be used to test the validity of the model [21]. Figure 1 presents block diagram of a typical workflow for SI.

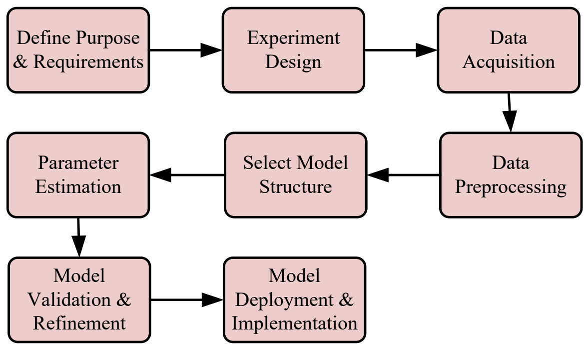

FIGURE 1. Typical Workflow for System Identification.

B. Machine Learning Approach

Electrical load modeling can be done using machine learning (ML), as it is a data-driven technique for modeling non-linear systems. With no prior knowledge of voltage, frequency, and power consumption, input and output data can be used to make a model and prediction [22]. A supervised learning technique such as Neural Network (NN), Linear Regression (LR), Support Vector Machine (SVM), or Decision Tree is used to predict load behavior after the accumulation of data is trained. By doing so, the model can simulate dynamics, predict loads, or improve control strategies and constitute a reliable and adaptable solution to the existing and demanding power systems [22]. ML can be described as a process for learning patterns from data by gradually building a predictive model in which, in a normal ML process, the required data is initially gathered and preprocessed to deal with problems like outliers, missing values, and noise. Next, features are engineered, usually using extra knowledge about the domain at a higher level in order to give a more appropriate representation of the patterns in the data [23]. The next step involves choosing an appropriate type of model say for example NN, SVM depending on the type of problem back-grounded again this step can be very time consuming and the final step involves training a model with a part of the data and then adjust the parameters of the model. Lastly, trained model prediction is tested on an unseen data set or a cross validation set to measure confidence and calibration of prediction in order to justify the reliability of the model [23]. Figure 2 presents block diagram of a typical workflow for ML.

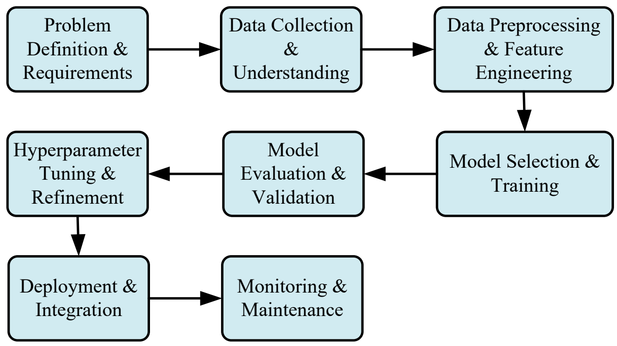

FIGURE 2. Typical Workflow for Machine Learning.

C. Design Process

Figure 3 presents a systematic approach for developing and validating a predictive model for load behavior in power systems, specifically targeting applications with variable hash rates, such as cryptocurrency mining. First, data is collected to adequately capture real-world conditions so they can be replicated in the model. The collected data is subjected to two distinct modeling methodologies: SI and ML.

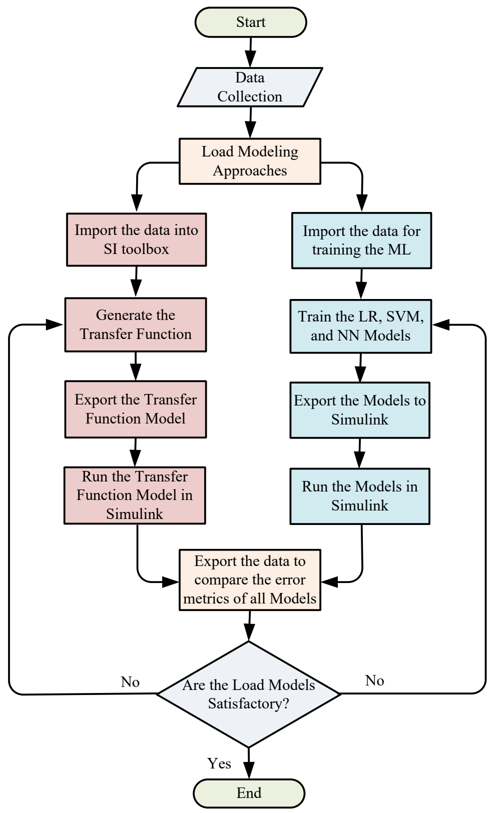

FIGURE 3. Flow chart of Load Modelling using SI and ML Approaches.

The SI approach imports the actual load data into MATLAB's SI Toolbox to generate a transfer function, as presented in Equation (1). It is subsequently tested in Simulink across various hash rates to evaluate its responsiveness after making trial-and-error adjustments. The ML approach used in this study is to train various models, including the LR, SVM, and NN Models, with the same dataset to generate an ability to predict output in MATLAB. Finally, a comparative evaluation using the Mean squared error (MSE), Mean absolute error (MAE), Coefficient of determination (R^2), Root mean squared error (RMSE), and Willmott's index of agreement (WIA) for each built model is performed. If the models show a good degree of accuracy, the values of R^2 and WIA are high, and RMSE, MSE, and MAE are low, the model is ready for deployment. Otherwise, gradual modifications are made to shape the model better. This double-throughput approach should help create a sound and stable indicative model that is flexibly load-forecast in response to fluctuating crypto mining load requirements, contributing to stable and efficient power supply regulation. Figure 4 presents the developed model of the flexible load.

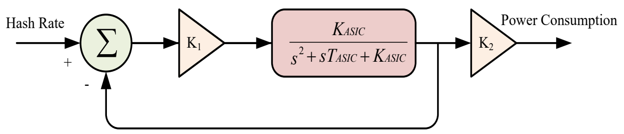

FIGURE 4.Flexible Load ASIC Model.

$$ASIC(s) = \frac{K_{ASIC}}{s^2+T_{ASIC}s+K_{ASIC}} \tag{1}$$

where k_1 represents the conversion gain between hash rate and proportional power, which is 1.6574, k_2 represents the conversion gain between per unit (PU) and the actual power value, which is 5000, K_{ASIC} represents the model gain, which is 0.00224, and T_{ASIC} represents the system's time constant, which is 0.06783.

III. LOAD MODEL VERIFICATION

To verify the performance of the developed load model, we integrated it into an island MG having multiple distributed generators, such as a diesel generator system and a wind turbine system, along with critical and non-critical loads. The proportional integral differential controller is designed using a genetic algorithm to get the optimal gain values for the controller.

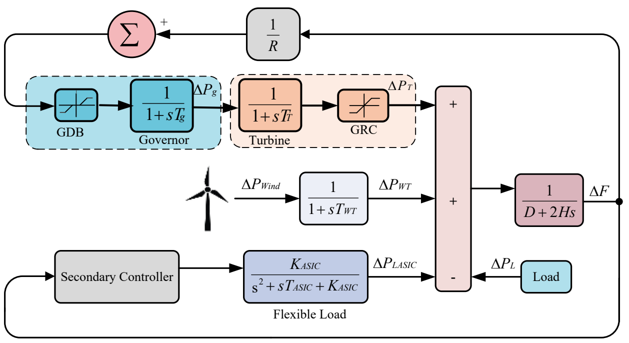

FIGURE 5. Islanded Microgrid Block Diagram Model.

The proportional integral differential controller controls the developed non-critical or flexible load. By doing so, the grid's stability will be efficiently maintained by harnessing surplus power during high-generation periods and reducing consumption during low-generation periods, thereby ensuring system stability and eliminating power waste. Figure 5 shows the block diagram of an Islanded MG model.

Where T_g represents the generator time constant, which is 0.1; T_T represents the turbine time constant, which is 0.4; T_{WT} represents the wind turbine time constant, which is 1.8; R represents the regulator of the generator, which is -2.4; D represents the damping coefficient, which is 0.1667, and H represents the inertia constant, which is 0.0075.

Scenarios associated with variable loads and variations in wind power system power generation are applied to the MG to examine and verify the performance of the developed flexible load model. Figures 6 and 7 present the results under different scenarios. The frequency deviation response caused by loads and wind generation changes was also presented.

Moreover, to further validate the findings' performance, we use statistical indices such as Mean squared error (MSE), Mean absolute error (MAE), Coefficient of determination (R^2), Root mean squared error (RMSE), and Willmott's index of agreement (WIA), as shown in Equations (2-6).

$$MSE = \frac{1}{m}\sum_{i=1}^{m} (y_i - \hat{y}_i)^2 \tag{2}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m} |(y_i - \hat{y}_i)| \tag{3}$$

$$R^2 = \frac{\frac{1}{m}\sum_{i=1}^{m} (y_i - \hat{y}_i)^2}{\frac{1}{m}\sum_{i=1}^{m} (y_i - \bar{y}_i)^2} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m} (y_i - \hat{y}_i)^2} \tag{5}$$

$$WIA = 1 - \frac{\sum_{i=1}^{m} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{m} (|\hat{y}_i - \bar{y}_i| + |y_i - \bar{y}_i|)^2} \tag{6}$$

This has been done by utilizing the actual load data and considering the load model data, LR model data, SVM model data, and NN model data as the individual predicted data. Table II presents the error metrics of all individual models.

TABLE II. EVALUATION METRICS OF ALL MODELS

Evaluation Metrics	*Load Model*	*LR Model*	*SVM Model*	*NN Model*
MSE	4650.095	5249.474	5394.844	2477.691
MAE	53.7996	54.551	58.7569	34.5373
R^2	0.9912	0.9901	0.9898	0.9953
RMSE	68.1916	72.4533	73.4496	49.7764
WIA	0.9978	0.9975	0.9975	0.9988

IV. RESULTS AND DISCUSSIONS

The developed flexible load model demonstrates strong alignment with actual load data, as shown in Figures 8 and 9, where the model closely tracks the performance of actual load data across varying operational conditions. The data presented in Figure 10 also shows high R^2 values for all three models: NN, LR, and SVM, which reflects near-perfect predictive accuracy. At the same time, the Load Model also shows high precision, albeit with a slightly lower R^2 of 0.9912 and WIE of 0.9978, compared to the NN model, as shown in Table II.

The observation from the RMSE, MSE, and MAE is that the NN model has the least mean error relative to the actual data, as presented in Table II, despite slightly higher RMSE, MSE, and MAE values of the Load model compared to the NN model, the LR, and SVM still exhibit good accuracy, validating their use for modeling load behavior in cryptocurrency mining applications, where load fluctuation patterns are critical. This flexible load model offers a novel solution for cryptocurrency mining applications by managing load consumption in response to power availability.

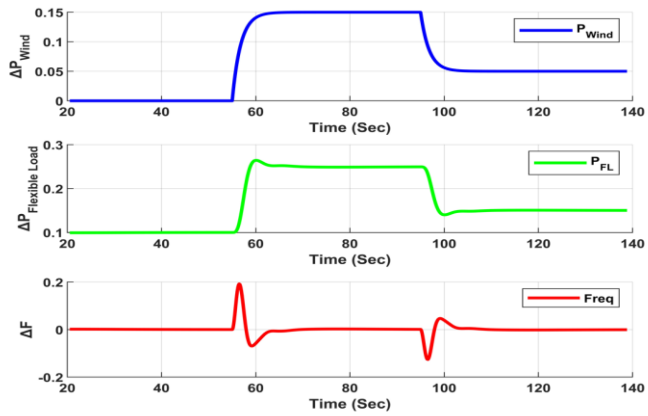

FIGURE 6. Dynamic Response of the Load Model under Wind Generation Change.

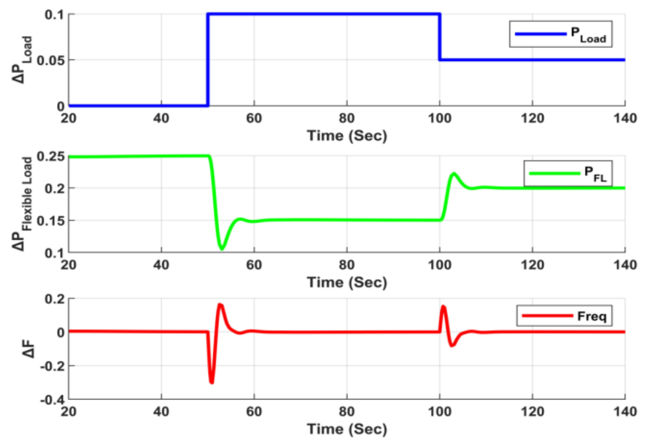

FIGURE 7. Dynamic Response of the Load Model under Load Demand Change.

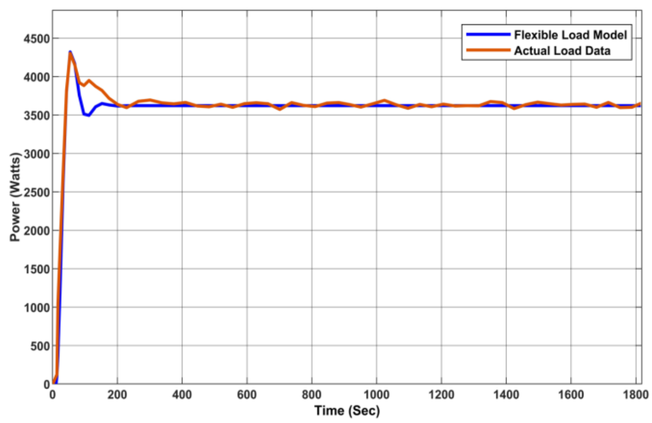

FIGURE 8. Flexible Load Model and Actual Load Data Performances.

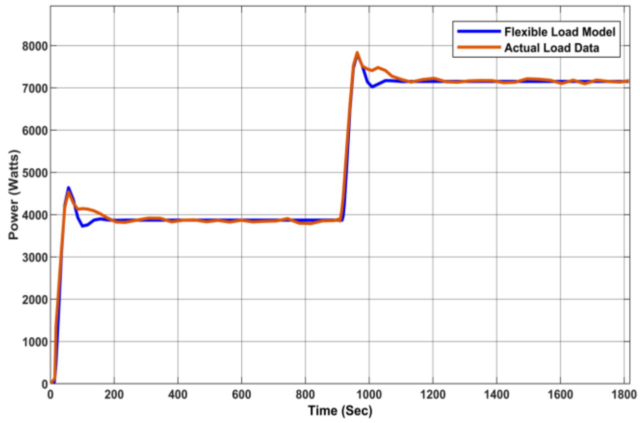

FIGURE 9. Flexible Load Model and Actual Load Data Performances Under Different Hash Rates.

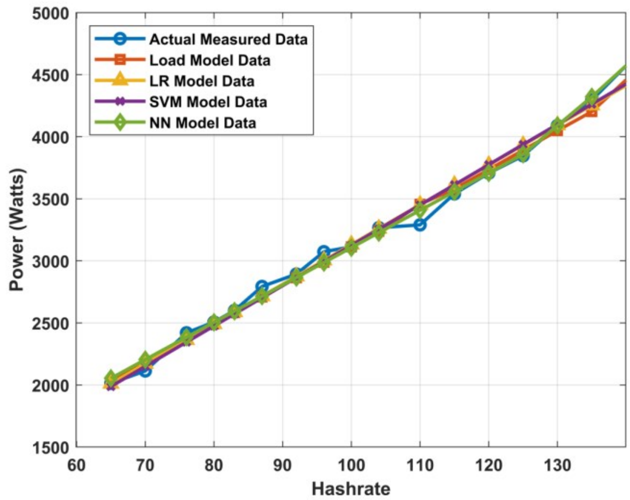

FIGURE 10. Regression Plots of all Models.

The model supports grid stability since it enables the miners to use surplus power during a high-generation period while a sparing use of power is used during a low-generation period. Such load flexibility is especially relished in systems with high RE generation where power availability can fluctuate. The adaptability contributes to the economy with renewable generation profiles by mitigating impacts from load variability and improving the stability and robustness of the power system.

V. CONCLUSIONS

The proposed load model designed and developed in this work is the Application-Specific Integrated Circuit, which is deemed a realistic and revolutionary approach to load management in cryptocurrency mining with high accuracy and dynamism in power conditions. Due to the flexibility created in load power consumption with power availability, the model ensures RES variability impediment, which is crucial in maintaining the grid's stability and efficiency. Cross-validation using SI and ML directions proves the model's steadiness; the NN Model has the greatest precision in capturing load actions. The proposed solution presents that miners can also serve as responsive loads and thus utilize more energy during periods of high supply and vice versa. This approach improves the grid's reliability and creates a benchmark for responsible energy use in load-demanding applications. Directions for the future include looking at how the model can be fine-tuned and extended to other flexible load contexts to enhance the overall contribution of the developed research to suitably facilitate and enhance sustainable energy application.

ACKNOWLEDGMENT

The author(s) express their gratitude for the support provided by the Renewable Energy Technical Incubator (RETI), sponsored by the National Industrial Development and Logistics Program (NIDLP), at the Interdisciplinary Research Centre for Sustainable Energy Systems (IRC-SES) at King Fahd University of Petroleum & Minerals (KFUPM) under the CREP 2522 project. On behalf of Md Shafiullah and Mohamed Zaery, the authors thank King Abdullah City for Atomic and Renewable Energy (K.A.CARE) for funding this work.

REFERENCES

[1] D. Fantazzini and N. Kolodin, "Does the Hashrate Affect the Bitcoin Price?," *Journal of Risk and Financial Management*, vol. 13, no. 11, p. 263, Oct. 2020, doi: 10.3390/jrfm13110263.

[2] E. Shanmuga Skandh Vinayak, N. Bhalaji, and X.-Z. Gao, "Analysis of Cryptocurrency Mining in Gaming Consoles," 2022, pp. 357–372. doi: 10.1007/978-981-19-0019-8_28.

[3] S. and Communication Networks, "Retracted: Mining Cryptocurrency-Based Security Using Renewable Energy as Source," *Security and Communication Networks*, vol. 2024, pp. 1–1, Jan. 2024, doi: 10.1155/2024/9808629.

[4] M. Zheng, G.-F. Feng, X. Zhao, and C.-P. Chang, "The transaction behavior of cryptocurrency and electricity consumption," *Financial Innovation*, vol. 9, no. 1, p. 44, Jan. 2023, doi: 10.1186/s40854-023-00449-7.

[5] A. Menati *et al.*, "High resolution modeling and analysis of cryptocurrency mining's impact on power grids: Carbon footprint, reliability, and electricity price," *Advances in Applied Energy*, vol. 10, p. 100136, Jun. 2023, doi: 10.1016/j.adapen.2023.100136.

[6] S. Ahmad Khan, "GROWTH OF CRYPTOCURRENCY AND ITS CHALLENGES." [Online]. Available: https://www.researchgate.net/publication/369507357

[7] R. Xie, W. Wei, M. Li, Z. Dong, and S. Mei, "Sizing capacities of renewable generation, transmission, and energy storage for low-carbon power systems: A distributionally robust optimization approach," *Energy*, vol. 263, p. 125653, Jan. 2023, doi: 10.1016/j.energy.2022.125653.

[8] J. Li, N. Li, J. Peng, H. Cui, and Z. Wu, "Energy consumption of cryptocurrency mining: A study of electricity consumption in mining cryptocurrencies," *Energy*, vol. 168, pp. 160–168, Feb. 2019, doi: 10.1016/j.energy.2018.11.046.

[9] J. Yang, J. Wu, T. Xian, H. Zhang, and X. Li, "Research on energy-saving optimization of commercial central air-conditioning based on data mining algorithm," *Energy Build*, vol. 272, p. 112326, Oct. 2022, doi: 10.1016/j.enbuild.2022.112326.

[10] Q. Zhang *et al.*, "A survey on data center cooling systems: Technology, power consumption modeling and control strategy optimization," *Journal of Systems Architecture*, vol. 119, p. 102253, Oct. 2021, doi: 10.1016/j.sysarc.2021.102253.

[11] P. Kushwaha, V. Prakash, S. Yamujala, and R. Bhakar, "Fast frequency response constrained electric vehicle scheduling for low inertia power systems," *J Energy Storage*, vol. 62, p. 106944, Jun. 2023, doi: 10.1016/j.est.2023.106944.

[12] A. Mohan, R. M. Shereef, and V. Vinod, "Improvement of frequency response in remote area power supply systems using ultracapacitor with enhanced inertia support controller," *Electrical Engineering*, vol. 106, no. 1, pp. 111–123, Feb. 2024, doi: 10.1007/s00202-023-01980-7.

[13] A. Mohan, R. M. Shereef, and V. Vinod, "Improvement of frequency response in remote area power supply systems using ultracapacitor with enhanced inertia support controller," *Electrical Engineering*, Aug. 2023, doi: 10.1007/s00202-023-01980-7.

[14] R. Mandal and K. Chatterjee, "Design of a maiden synthetic inertia controller using super-capacitor energy storages and electric vehicles and real-time validation of the performance of the controller," *J Energy Storage*, vol. 55, p. 105559, Nov. 2022, doi: 10.1016/j.est.2022.105559.

[15] S. Oshnoei, M. Aghamohammadi, S. Oshnoei, A. Oshnoei, and B. Mohammadi-Ivatloo, "Provision of Frequency Stability of an Islanded Microgrid Using a Novel Virtual Inertia Control and a Fractional Order Cascade Controller," *Energies (Basel)*, vol. 14, no. 14, p. 4152, Jul. 2021, doi: 10.3390/en14144152.

[16] M. Aly, E. A. Mohamed, A. M. Noman, E. M. Ahmed, F. F. M. El-Sousy, and M. Watanabe, "Optimized Non-Integer Load Frequency Control Scheme for Interconnected Microgrids in Remote Areas with High Renewable Energy and Electric Vehicle Penetrations," *Mathematics*, vol. 11, no. 9, p. 2080, Apr. 2023, doi: 10.3390/math11092080.

[17] K. Y. Yap, C. R. Sarimuthu, and J. M.-Y. Lim, "Virtual Inertia-Based Inverters for Mitigating Frequency Instability in Grid-Connected Renewable Energy System: A Review," *Applied Sciences*, vol. 9, no. 24, p. 5300, Dec. 2019, doi: 10.3390/app9245300.

[18] A. Sauhats, A. Utans, J. Silinevics, G. Junghans, and D. Guzs, "Enhancing Power System Frequency with a Novel Load Shedding Method Including Monitoring of Synchronous Condensers' Power Injections," *Energies (Basel)*, vol. 14, no. 5, p. 1490, Mar. 2021, doi: 10.3390/en14051490.

[19] V. Rajaguru and I. Annapoorani, "Automatic Load Frequency Control in an Isolated Micro-grid with Superconducting Magnetic Energy Storage Unit using Integral Controller," *J Phys Conf Ser*, vol. 1969, no. 1, p. 012032, Jul. 2021, doi: 10.1088/1742-6596/1969/1/012032.

[20] S. Yıldız, H. Gunduz, B. Yildirim, and M. Temel Özdemir, "An islanded microgrid energy system with an innovative frequency controller integrating hydrogen-fuel cell," *Fuel*, vol. 326, p. 125005, Oct. 2022, doi: 10.1016/j.fuel.2022.125005.

[21] E. Gincsainé Szádeczky-Kardoss, T. Varga-Berta, B. Kiss, and C. Fazekas, "Sensor Selection for Mechatronic Systems Based on Closed-Loop Control Simulations," in *25th International Symposium on Measurements and Control in Robotics*, I. Doroftei, B. Kiss, Y. Baudoin, Z. Taqvi, and S. Keller Fuchter, Eds., Cham: Springer Nature Switzerland, 2024, pp. 107–117.

[22] K. Goswami and A. B. Kandali, "Machine learning algorithms for predicting electrical load demand: an evaluation and comparison," *Sādhanā*, vol. 49, no. 1, p. 40, Jan. 2024, doi: 10.1007/s12046-023-02354-2.

[23] M. M. Taye, "Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions," *Computers*, vol. 12, no. 5, p. 91, Apr. 2023, doi: 10.3390/computers12050091.