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

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Outlines

- Motivation
- Demand Side Management
- Load Model
- Load Model Verification
- Results and Discussion
- Conclusion

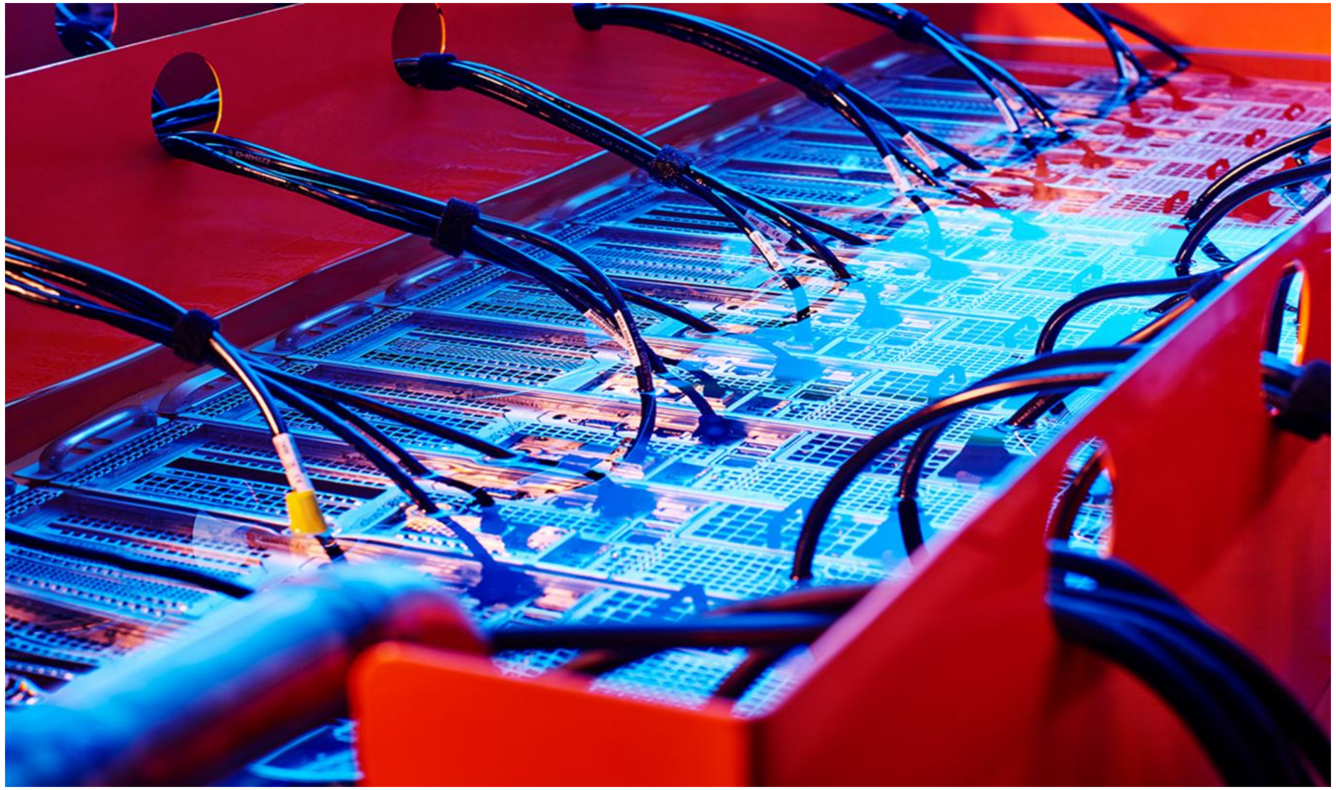
Motivation

- Mining cryptocurrency has been recognized as an essential part of blockchain networks.

- Hash rate and power consumption exhibit a direct correlation, as increasing computational power typically requires higher energy consumption.

Motivation

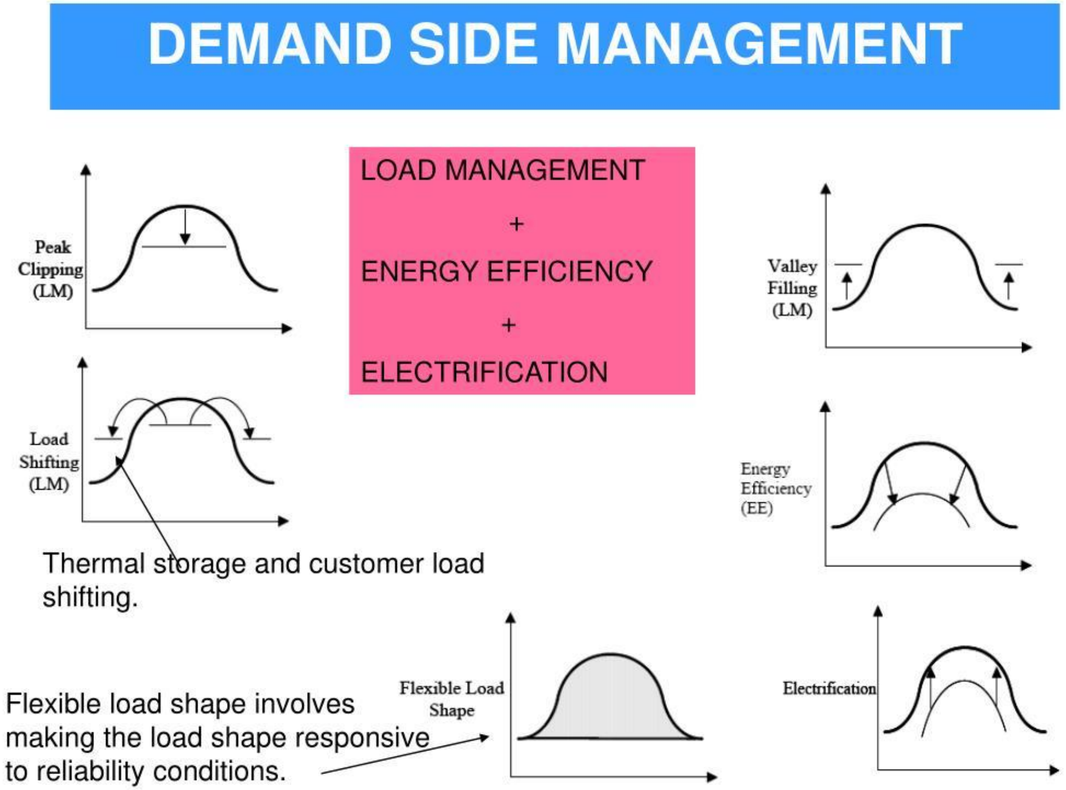
- Efficient mining hardware allows miners to achieve higher hash rates with lower power consumption.
- The cryptocurrency mining loads can be integrated into the modern power system to serve as demand side management.



Demand Side Management

- Cryptocurrency mining loads can play a significant role in demand-side management . It has following advantages:

1. Flexible Load Management
2. Peak Load Reduction
3. Valley Filling
4. Integration of Renewables
5. Load Shifting
6. Enhance Grid Reliability
7. Maintain the Grid Stability, etc.



Load Model Approaches

- To develop the load model the following approaches were used:

1. System Identification and
2. Machine Learning

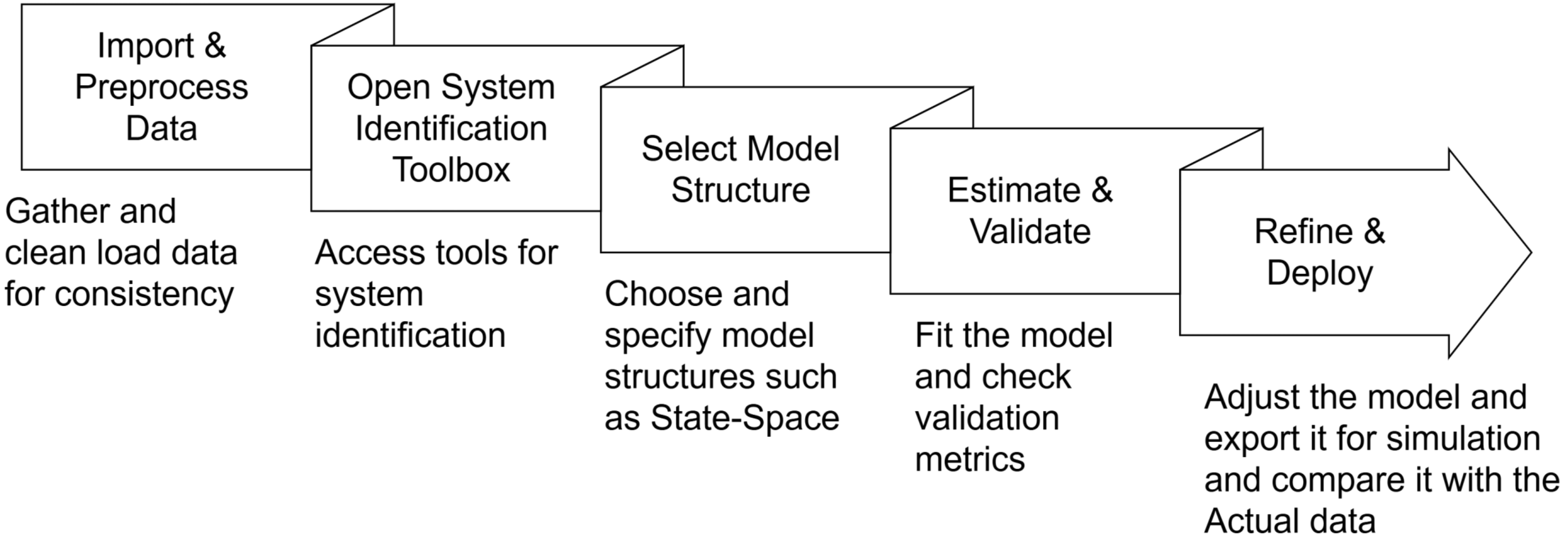
- The actual operational dataset of 1,289 rows and 4 columns was used for identification and training.

Time	Miner 1 Powe	Miner 2 Power	Total Power	Miner 1 Hashrate	Miner 2 Hash Rate	Total Hashrate
19:28:41	212.7733333	216.6253918	429.3987251	0	0	0
19:28:42	214.88	216.5752014	431.4552014	0	0	0
19:28:43	200.1333333	216.525011	416.6583443	0	0	0
19:28:44	221.2	216.4748206	437.6748206	0	0	0
19:28:45	206.4533333	216.4246302	422.8779635	0	0	0
19:28:46	383.6813873	217.2276767	600.909064	0	0	0
19:28:47	1227.950983	217.1774863	1445.128469	0	0	0
19:28:48	1236.377649	217.1272959	1453.504945	0	0	0
19:28:49	1219.786975	217.0771055	1436.86408	16.78963434	0	16.78963434
19:28:50	1177.916301	217.0269151	1394.943216	18.76186093	0	18.76186093
19:28:51	1182.129634	216.6253918	1398.755026	21.02045766	0	21.02045766
19:28:52	1175.809634	216.5752014	1392.384835	22.90443492	0	22.90443492
19:28:53	1275.878998	216.525011	1492.404009	25.11650114	0	25.11650114
19:28:54	1542.905742	216.4748206	1759.380562	24.41121577	0	24.41121577
19:28:55	1584.513757	216.4246302	1800.938387	27.64138932	0	27.64138932
19:28:56	1761.741811	217.2276767	1978.969488	27.32678988	0	27.32678988
19:28:57	2034.825896	217.1774863	2252.003382	33.42820641	0	33.42820641
19:28:58	2032.719229	217.1272959	2249.846525	34.4932323	0	34.4932323
19:28:59	2022.448555	217.0771055	2239.52566	35.86692312	0	35.86692312
19:29:00	2189.143276	217.0269151	2406.170191	34.39531744	0	34.39531744
19:29:01	2193.356609	217.0771055	2410.433714	36.20571199	0	36.20571199
19:29:02	2355.837996	217.0269151	2572.864911	37.42544982	0	37.42544982
19:29:03	2458.014027	216.9767247	2674.990752	43.02547606	0	43.02547606
19:29:04	2597.847399	216.9265343	2814.773933	43.64172692	0	43.64172692
19:29:05	2691.596763	216.8763439	2908.473107	44.54821723	0	44.54821723
19:29:06	2764.542119	216.8261535	2981.368273	43.70606377	0	43.70606377

Load Model

Modeling Cryptocurrency Mining Load Using <u>System Identification</u>

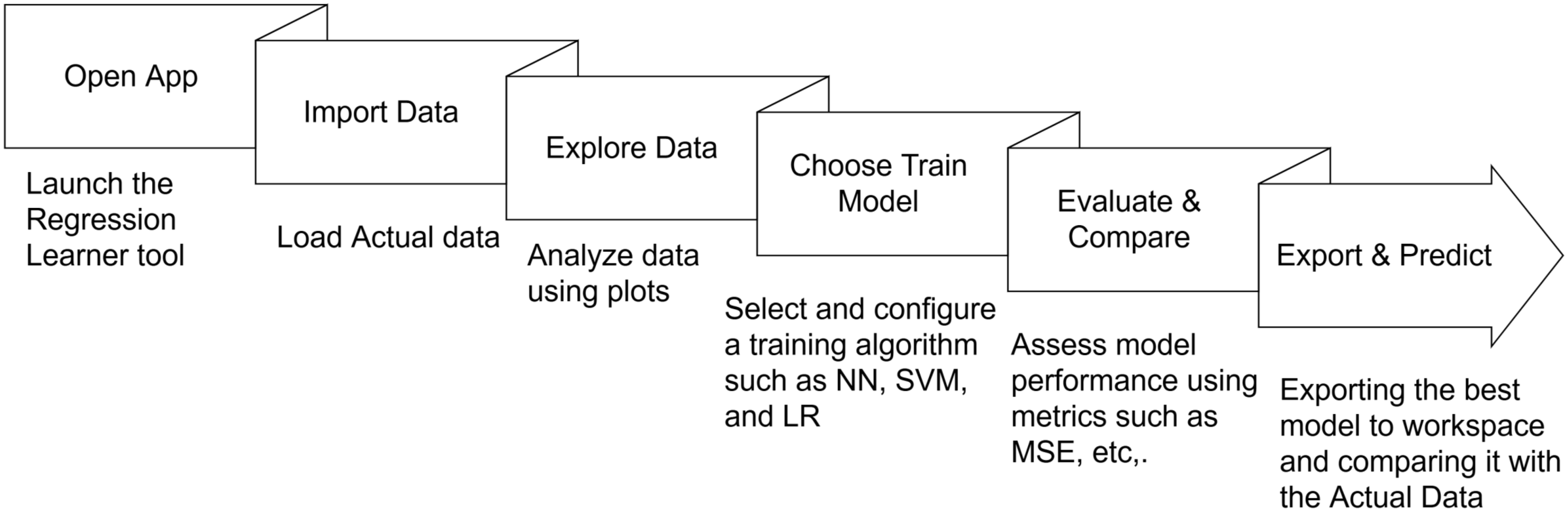
System Identification Process



Load Model

Modeling Cryptocurrency Mining Load Using **Machine Learning**

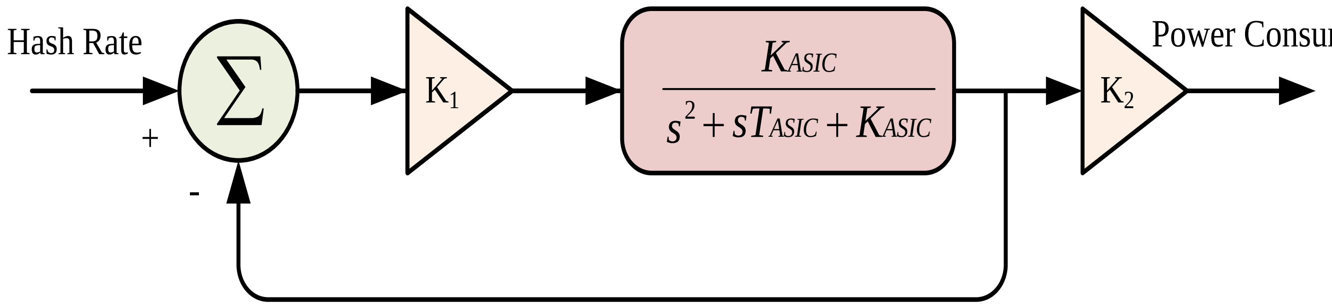
Machine Learning Workflow in MATLAB



Load Model

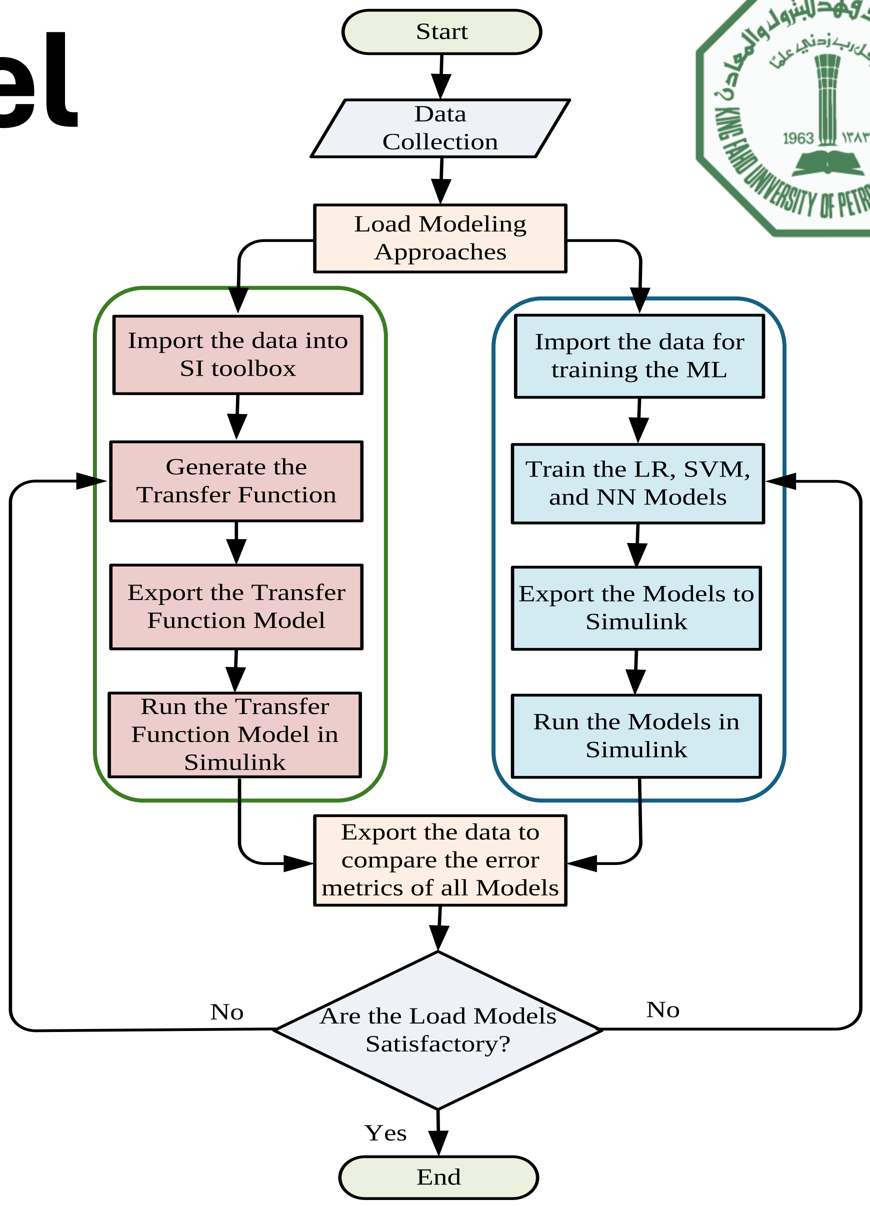
- The developed model provided a replica of the actual operational data of the system data with minimal error.

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



Flexible Load Model

- To validate the developed load model, we remodel the load using LR, SVM, and NN models and made a comparison.



Flow chart of Load Modelling using SI and ML Approaches

Load Model

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.

Results and Discussions

- The load model offers a novel solution for cryptocurrency mining applications by managing the power load consumption in response to power availability
- It enables miners to use surplus power during high-generation periods and cut power consumption during low-generation periods, enhancing grid stability
- The results demonstrate identical performance for the load model and operational data

Results and Discussions

- 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)
- The Load Model shows high precision, although it has a slightly lower R^2 of 0.9912 and WIE of 0.9978, compared to the NN model

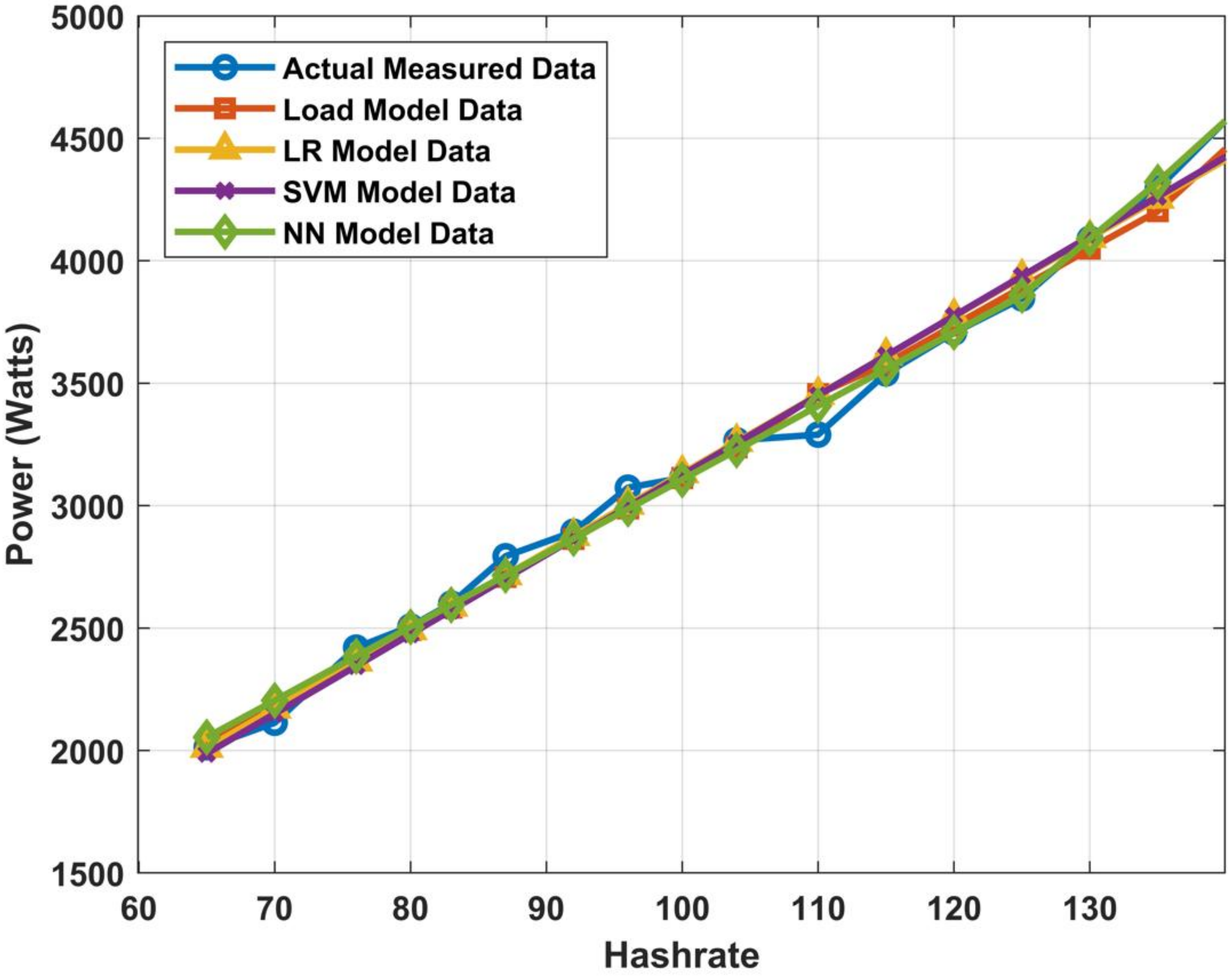
Results and Discussions

Verifying the load model using actual operational data and predicted machine learning models under different harsh rate

Hashrate	Measured Power	Load Model Power	LR Model Power	SVM Model Power	NN Model Power
65	2013.33	2023.50	2010.5	1987.7	2053.8
70	2113.33	2179.45	2170.7	2150.2	2204.2
76	2420.00	2367.50	2362.9	2345.2	2384.7
80	2506.67	2492.20	2491.1	2475.2	2505
83	2600.00	2584.50	2587.2	2572.6	2595.3
87	2793.33	2708.50	2715.3	2702.6	2715.6
92	2893.33	2864.00	2875.5	2865.1	2866
96	3073.33	2988.50	3003.6	2995.1	2986.3
100	3113.33	3113.33	3131.8	3125	3106.6
104	3266.67	3237.50	3259.9	3255	3226.9
110	3290.00	3455.50	3452.2	3450	3407.4
115	3540.00	3580.02	3612.3	3612.4	3557.8
120	3706.67	3735.75	3772.5	3774.9	3708.2
125	3846.67	3891.50	3932.7	3937.4	3858.6
130	4090.00	4049.00	4092.9	4099.9	4090
135	4294.67	4202.50	4253.1	4262.3	4321.5
140	4573.33	4458.25	4413.3	4424.8	4573.3

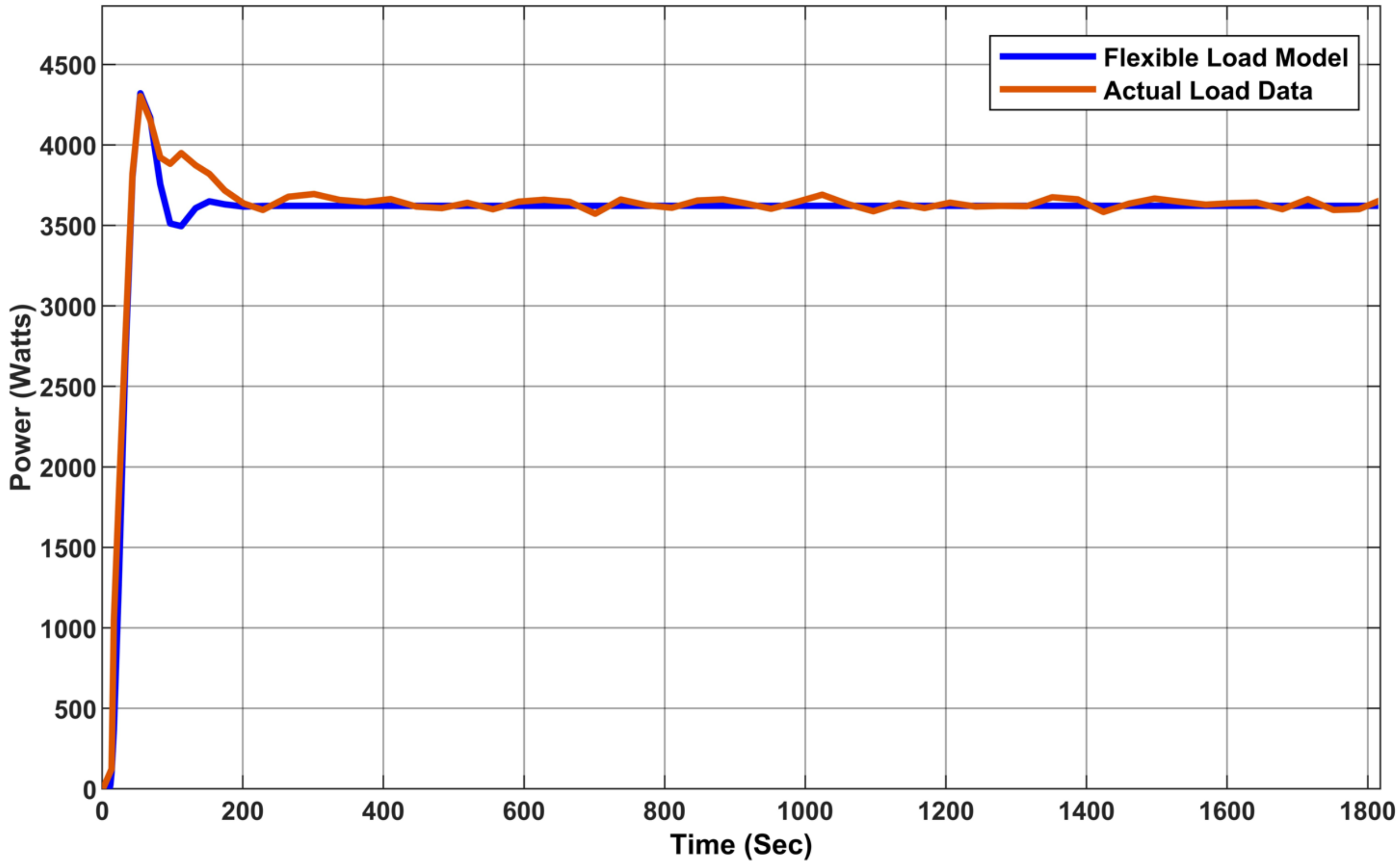
Results and Discussions

Scatter plot of actual and developed models



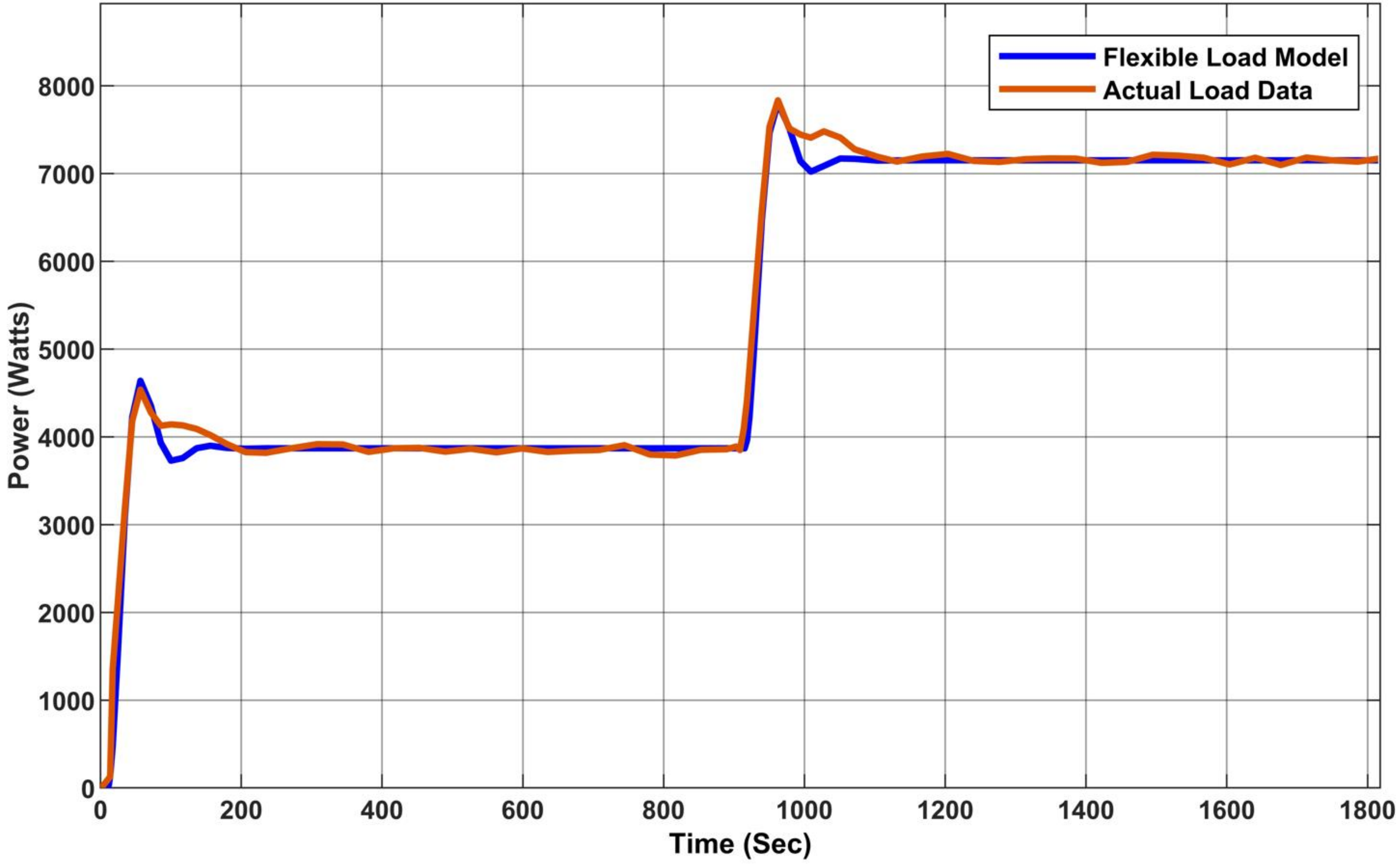
Results and Discussions

The load model performance under single hash rates



Results and Discussions

The load model performance under different hash rates

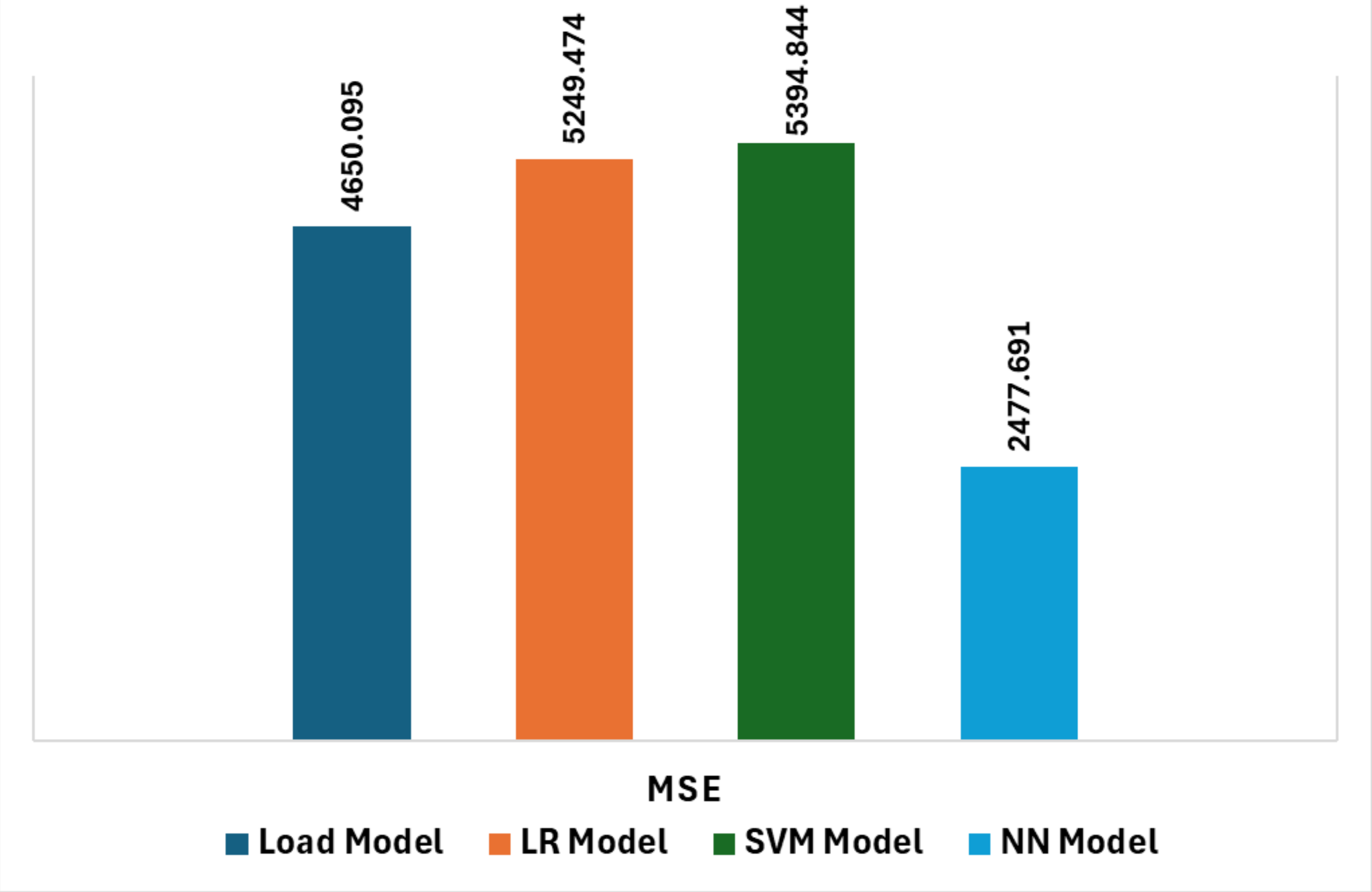


Results and Discussions

Results validation using MSE statistical indices

To validate the findings, the following statistical indices was used.

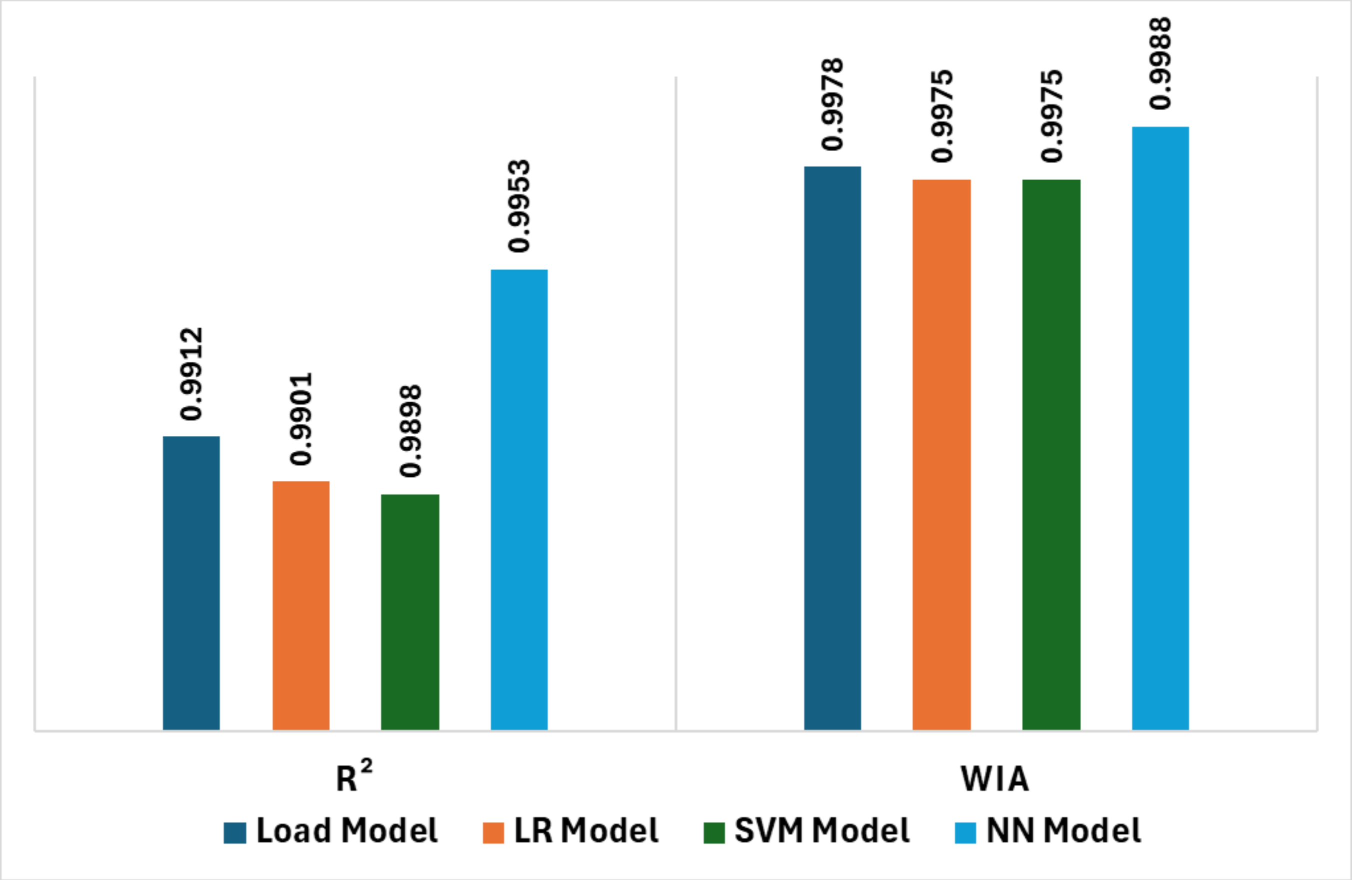
1. Mean squared error (MSE)
2. Coefficient of determination (R2)
3. Willmott's index of agreement (WIA)
4. Mean absolute error (MAE)
5. Root mean squared error (RMSE)



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

Results and Discussions

Results validation using WIA & R^2 statistical indices

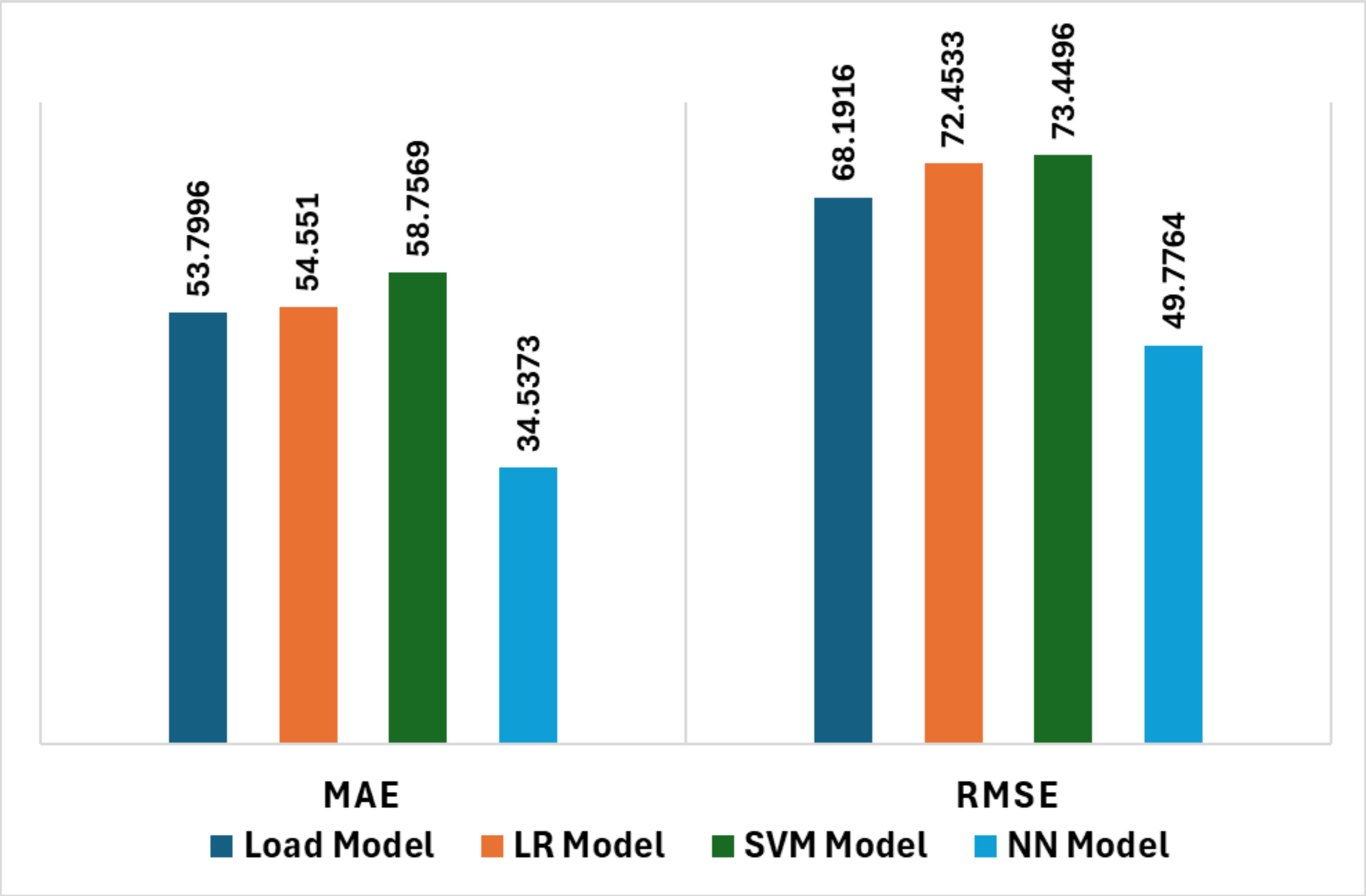


$$WIA = 1 - \frac{\sum_{i=1}^{m} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{m} (|\hat{y}_i - \bar{y}_i| + |y_i - \bar{y}_i|)^2} \qquad (3)$$

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

Results and Discussions

Results validation using MAE & RMSE statistical indices



$$MAE = \frac{1}{m}\sum_{i=1}^{m} |(y_i - \hat{y}_i)| \qquad (5)$$

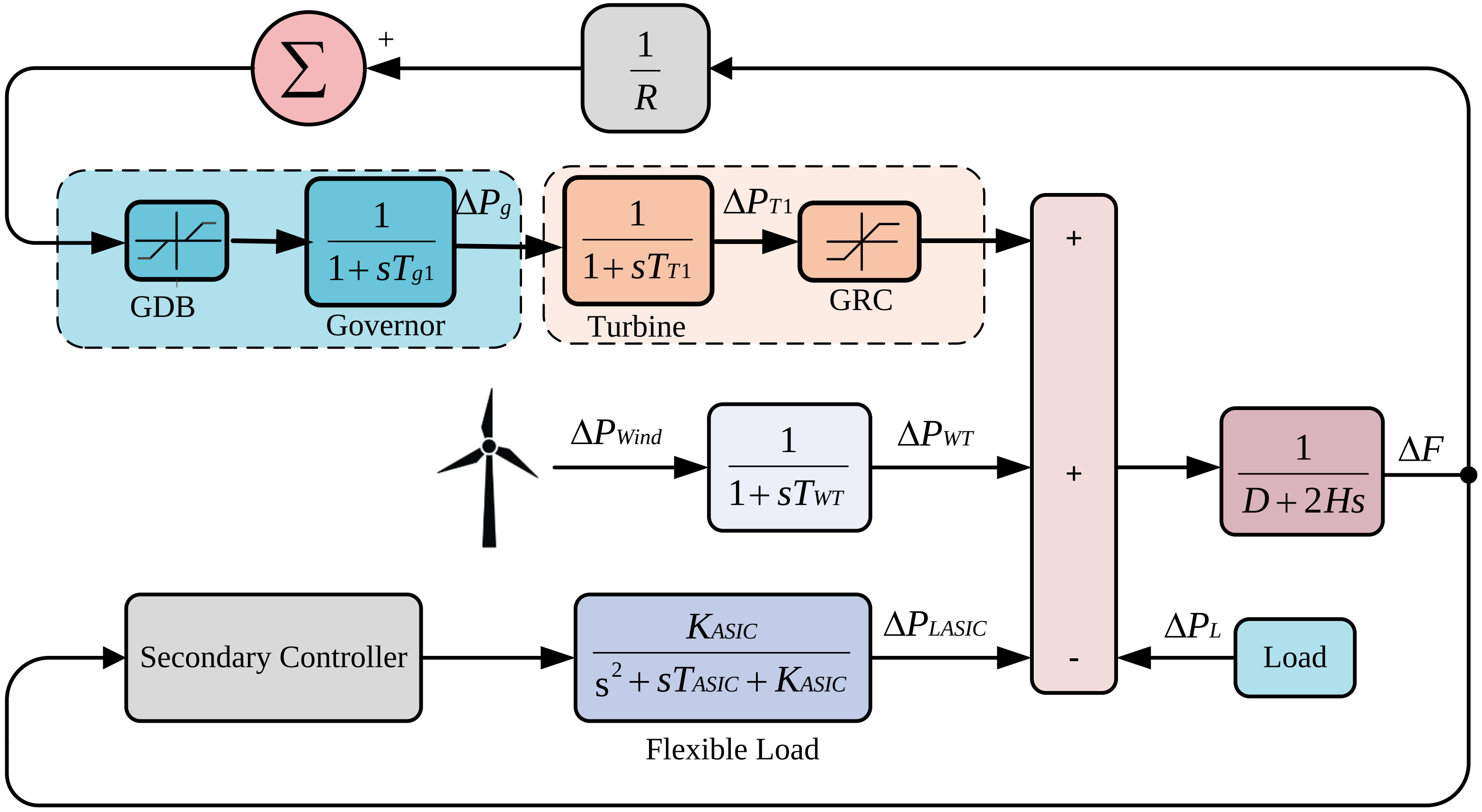
$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m} (y_i - \hat{y}_i)^2} \qquad (6)$$

Load Model Verifications

- To verify the performance of the load model further, we integrated it into an island microgrid with multiple distributed generators, such as a diesel generator system and a wind turbine system, along with the critical load.
- Load frequency control is necessary for microgrids to maintain system stability, balance supply and demand, support grid integration, and minimize frequency deviations.

Load Model Verifications

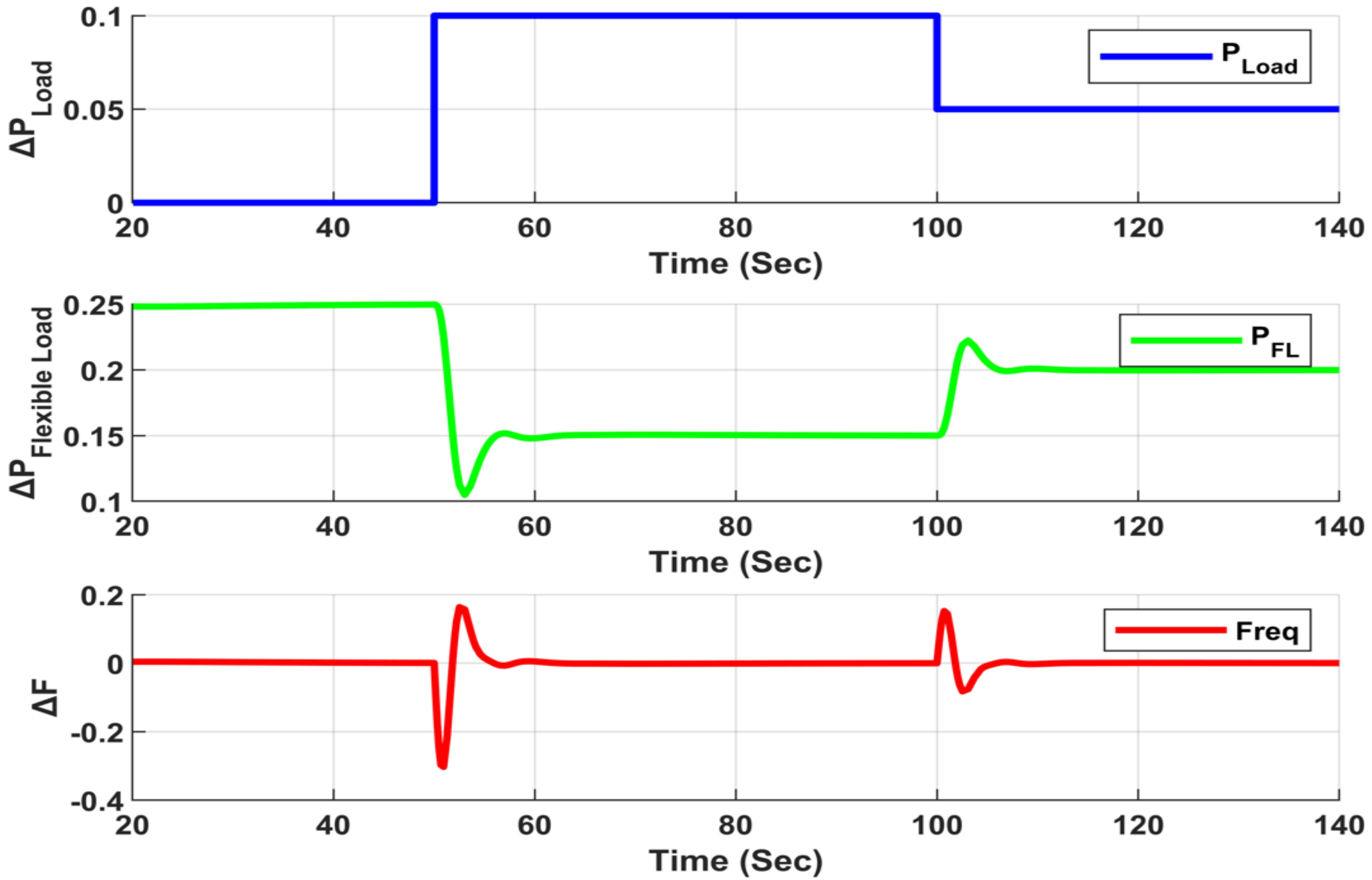
The PID controller is designed and cascaded with the load model to form a secondary control loop in the system.



Islanded Microgrid Block Diagram Model

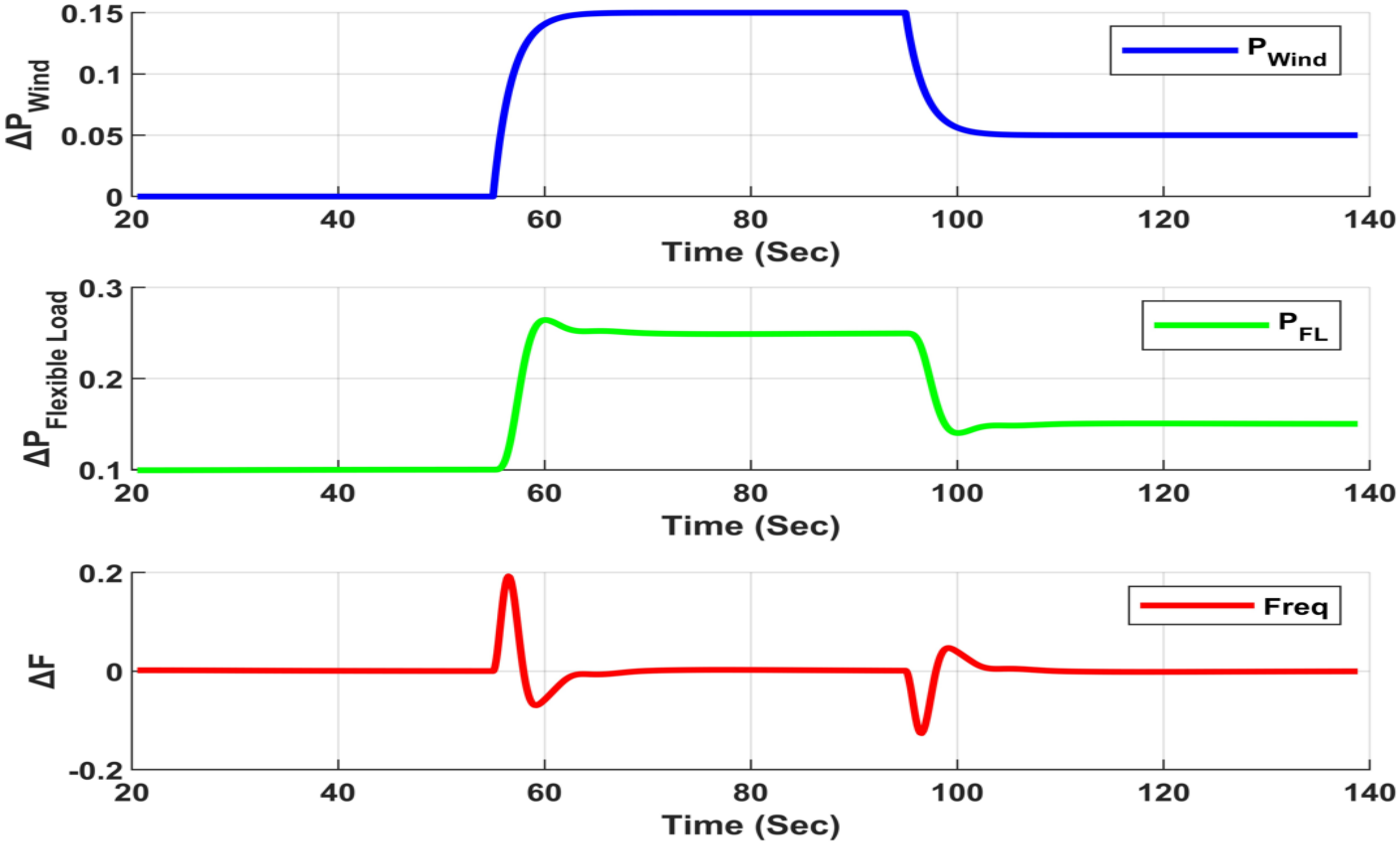
Load Model Verifications

"Different Loading Conditions"



Load Model Verifications

"Variation in Wind Generation"



Conclusion

- The work presents a flexible load model, a revolutionary approach for cryptocurrency mining.
- It offers high accuracy and flexibility in power conditions, ensuring grid stability and efficiency.
- Flexibility in load power consumption with power availability prevents RES variability challenge.
- Miners can serve as responsive loads, utilizing more energy during high generation periods.

Conclusion

- Cross-validation using machine learning and statistical indices to confirme model's stability.
- NN Model captures load actions with high precision.
- Verifying the performance of the developed load model by integrating it into microgrid.
- Improves grid reliability and sets a benchmark for responsible energy use in load-demanding applications.
- Future directions include fine-tuning and extending the model to other flexible load contexts.

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