Decentralized IoB for Influencing IoT-based Systems Behavior

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***Abstract*—Recently, IoT devices have become affordable to support various types of applications which have encouraged their usability in data collection, behavior tracking, and pattern analysis to gain knowledge to achieve certain goals. The Internet of Behavior (IoB) allows organizations and individuals to achieve all of this simultaneously. Various technologies and approaches can be used to support IoB systems to operate efficiently, such as 6G networks and decentralized systems structure that support IoT-based systems to distribute operations across devices and influence each device individually. Therefore, this paper proposes a decentralized IoB framework for achieving energy sustainability by tracking, analyzing, and influencing IoT devices' behavior. The collected results from an extensive decentralized IoB electrical power consumption experiment show that the decentralized system achieved higher accuracy compared to the centralized system, thus sending 3.5% fewer alerts and saving 3.4% more power for 3 sub-meters over a period of 500 hours.**

***Index Terms*—IoB, Decentralized systems, IoT, Deep Learning.**

I. Introduction

Advances in communications and computing have made it possible for several emerging technologies to be integrated within any type of application and service. One particular area (i.e., Internet of Things (IoT)) has witnessed great development due to its endless benefits to many systems. IoT devices are no longer simple end-user devices, on the contrary, they are becoming intelligent devices that are capable of real-time processing, monitoring, and take important decisions. It is also expected that the industrial IoT market growth will be $22.48-$29.3 billion intelligent internet-connected devices by 2023 [1][2].

One very unique aspect of employing intelligent IoT devices, is not only in objects monitoring, but also in tracking people's behaviors. Having abundant number of IoT devices, continuously processing real-time data, alongside their smart features through the use of Artificial Intelligent (AI) applications, IoT would play a major role in detecting people's behavior. This is a new emerging concept called the Internet of Behavior (IoB). *Gote Nyman* announced the concept of IoB term back in 2012. IoB is interested in detecting human behavioral pattern from devices (e.g. IoT) by analyzing the history of patterns in fields of business, society, health, politics, and many other ones. IoB can be very useful in certain cases and very harmful and malicious to users' privacy and their behaviors [3].

IoB relies on the use of AI, distributed computing, IoT, and the user's active cooperation in simple/complex internet activities. Each IoT device will represent a user's behavior. This seems great, but at the same time risky if the collected learning is used to control the user's future actions for certain benefits which the user is not aware of or consent to. Each IoB will have certain characteristics based on different psychological criteria. The usefulness and capabilities of the behavior are determined according to certain psychological characteristics.

Since IoT devices (e.g. smartphones, home cameras, general surveillance devices) belong to end-users, who in reality are human beings, devices tend to carry over similar characteristics of the user. People, in reality, differ in their characteristics, for example, one person might be open to others, while another is more conservative. A person's willingness to share something might be motivated by his/her emotion. Such psychological characteristics of humans are the driving force behind IoB system. By applying five personality criteria to IoT devices, namely, *cognition*, *emotion*, *behavior*, *personality*, and *inter-communication*, an IoB system will be developed to determine the worthy value of a certain behavior and how far it can be controlled. In the following sub-sections, we describe each criterion, its short- and long-term impact on IoB state, and the dependency of each criterion on the rest of the criteria.

i) *Cognition*: Cognition is defined as the node's ability to evaluate different situations (i.e. network behavior and surrounding contextual state), then as a result take an action.

ii) *Emotion*: Emotion is the instinctive feelings derived from the current personal and surrounding state. For instance, if the user had a busy work schedule, then according to the gathered history, it is determined that the IoT resources are free of use and it is highly probable that the IoT is willing to cooperate or share its resources due to having the user rest for a certain time according to his schedule.

iii) *behavior*: behavior is the way in which an IoT tends to act at different states. Such actions taken are highly dependent on the other criteria.

iv) *Personality*: Personality is highly related to user's personal characteristics. For instance, a person who is highly aggressive in nature would also result in having the node to act aggressively.

v) *Inter-Communication*: The tendency of an IoT to communicate with other IoTs is defined as inter-communication.

Such characteristic is not only dependent on the other criteria, but is also dependent on the devices capabilities.

This paper proposes a decentralized IoB framework for achieving energy sustainability by tracking, analyzing, and influencing IoT devices' behavior. The goal of this framework is to change consumer behavior into an eco behavior to reduce power consumption, and therefore reduce power waste and cost. This framework integrates IoT, AI, Data Analytics, and Behavioral Science techniques to achieve user and business benefits. The framework has been extensively tested in a decentralized environment, compared to a centralized one, and shows how influencing users' behaviors improves power and costs. The contributions of this paper can be summarized as follows:

- Propose a novel decentralized IoB framework for achieving energy sustainability by influencing IoT devices behavior.
- Implement an experiment for power consumption decentralized IoB system with advanced deep learning and predictive model architecture to influence smart electrical meters consumption to control the excessive consumption behavior.
- Present an extensive evaluation for the proposed decentralized system compared to a centralized system in the area of energy consumption.

II. Related Work

While influencing user's behavior through the use of IoT devices appears to be a low-risk effect compared to mortality or economic disaster, it is powerful enough to create higher risks ranging from controlling crowd to manipulating individuals' tastes. For example, in a study carried by S. Stack [4] about the effect of social distancing on suicide rates, the results showed that a change in the social distancing index of ten units caused a 2.9% increase in the suicide rate. Moreover, during the global COVID19 pandemic, several studies conducted in the US have shown that wearing masks could lower deaths, saving $\approx 130,000$ lives [5][6].

The widespread of Coronavirus has speeded up and given technology providers the means to actively track people's movements. Once tracking and recording user's IoT activities (real-time), deducing their behavior becomes crucial to influence it in adverse situations. For example, using machine learning for mask recognition tasks is one way to get individuals to respect regulations and to help monitor their negligence [7].

Attempting to influence and change user behavior is sensitive, as it may encounter resistance and other psychological factors related to comfort and trust. Emerging technologies such as XAI will help the user with the required understanding and trust of any system that uses AI models. XAI aims to use methods and techniques to explain to the user what an AI model does and why, thus giving a better perception of system operations. Therefore, the process of tracking, analyzing, and influencing user behavior will become much simpler [3][8][9].

In their study to predict power consumption [10][11], Syed, proposed a framework consisting of data cleaning and model building steps. Whereas the study of Kim, Lee, aimed to accelerate the deployment process of deep learning models using the proposed edge-cloud framework.

Additionally, the authors of [12] and [13], have applied Deep Reinforcement Learning algorithms (Deep RL) to perform tasks related to process optimization of power consumption. While Liu, Zhang, and Gooi focused on the proposed RL model structure, Chung, Maharjan, Zhang, and Eliassen proposed a stochastic game framework that controls the interaction between the consumed power and household.

III. Decentralized IoB for Power Sustainability: A Framework

Intending to achieve energy sustainability through stable and high fault-tolerant techniques, this section proposes a decentralized IoB framework that influences smart electrical IoT devices behavior to control excessive power consumption. The goal is to control the energy consumption of home appliances automatically and effortlessly without any human interaction by controlling the smart electric meters connected to each home appliance.

The framework architecture in Figure 1 shows that each appliance will be connected to an IoT smart meter connected to a cloud service via an IoT network. Each smart meter will monitor the power consumption of the connected appliance, calculate the consumed energy every hour, and then send the consumption amount to the cloud via an IoT gateway.

The cloud service is the brain of the framework where it produces the action that the framework parts should follow. The data received by each smart meter will be stored in a fast, reliable, and scalable database that processes a massive amount of raw data such as MongoDB. Then, the data will be preprocessed by an edge device before getting to the server to handle the lost data that occurs from the unstable connection, remove outliers, clean and scale the data to the same range, and transform the data into a suitable format for the AI model. Then, the AI model will use the preprocessed data to predict the power consumption in the next hour. The AI model will be in a robust architecture that deals with multiple inputs and outputs of time series data. A scalable and Python-compatible deep learning framework that provides excellent functionality should be used to build this AI model.

Then, the controller subsystem will use the AI model prediction and historical data patterns to determine the amount of power to be consumed in the next hour by analyzing the appliance behavior. Both preprocessing phase and the controller will be built in a productive and fast programming language which supports a large number of libraries, and possesses strong integration, such as Python. When the controller decides the amount of power to be consumed in an over-consumption prediction case by any connected appliance, it will send an alert to the connected smart meter via the network with the consumption amount threshold. Thus, the smart meter that has excessive consumption behavior will control the amount of consumption of its connected devices.

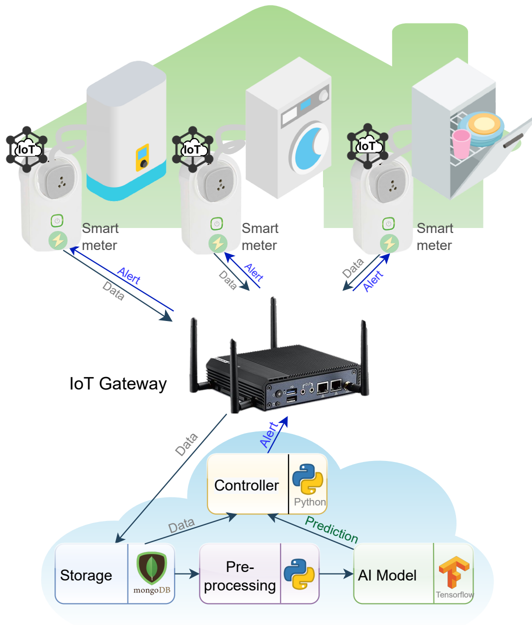


Fig. 1. Framework Architecture

Accordingly, analyzing appliances' power consumption behavior through historical and real-time data generated by connected IoT smart meters to detect excessive consumption, and then controlling the consumption amount will reduce the power consumption. As a result, power efficiency and sustainability are achieved through a comprehensive decentralized system that has more stability, works with every connected IoT individually, and eliminates the single point of failure issue.

IV. Experimental Implementation

An experiment was conducted to implement the proposed framework by building a distributed IoB system for achieving power efficiency through influencing the behavior of IoT devices. First, the dataset was reprocessed. Second, a time series prediction model was developed. Next, a system controller was implemented to analyze and control the behavior of IoT devices. Finally, four time-series prediction models for a centralized IoB system structure were created to compare the performance of the models with that of the decentralized prediction model.

A. Dataset and Data Pre-processing

A french household electrical power consumption data was used to carry out the experiment [14]. It consists of measurements for electrical power consumption per minute sampling rate over a period of about four years. The dataset features include data and time, global active power, global reactive power, voltage, global intensity, sub metering 1, sub metering 2 and sub metering 3. The focus of this experiment is on global active power and 3 sub-meters that produce IoT data which corresponds to:

- *Global active power*: Global house power consumption of active power.
- *Sub metering 1*: Kitchen power consumption, mainly a dishwasher.
- *Sub metering 2*: Laundry room power consumption, mainly a washing machine.
- *Sub metering 3*: Electric water heater and air-conditioner.

Since the framework operates for hourly power consumption, the dataset was re-sampled for power consumption per hour sampling rate in the data preprocessing phase. The dataset also contains null values for approximately 1.25% of the rows. Thus, the null values were replaced by the mean of the values. Finally, the dataset was scaled to the same range using MinMaxScaler. The dataset was divided into 26,280 hours of training and 8,308 hours of testing.

B. Sequence-to-Sequence Autoencoder

The proposed framework has a distributed architecture over different house appliances sub-meters to control the power consumption. Therefore, an appropriate deep learning model needs to be built to support the distributed architecture of the system.

According to the framework, the AI model will receive values from each smart-meter individually, and the total active power will be calculated to support the model's learning process. Also, the model will predict the power consumption of each connected smart-meter. Accordingly, a sequence to sequence encoder-decoder architecture was used to build the deep learning model since this architecture supports the nature of the proposed framework by receiving a sequence of input features and predicting a sequence of outputs. Figure 2 illustrates the structure of the built model. Long-short-term-memory (LSTM) cells were used to construct the encoder and decoder with 100 units, tanh activation function, and return the last state. Also, the decoder was supported with a repeated vector layer to repeat the incoming input from the encoder to push it to the decoder and a time distributed dense layer to apply it to each input sample, thus decoding the output sequence.

Tensorflow deep learning framework and Keras library were used to build the model on a 2.3 GHz CPU with Intel processor and 13 gigabyte RAM machine. The model was run for 20 training epochs with a "mean_squared_error" loss function and "Adam" optimization function.

C. System Controller

The proposed framework predicts the hourly power consumption of each connected appliance and controls the amount of power consumed to a specific threshold, thus saving a specific amount of power. If the predicted power consumption of each appliance is higher than its average consumption pattern, the controller will send the amount of power that needs to be consumed to the smart-meter to control the consumption of that appliance.

For each time the AI model predicts a higher power consumption of an appliance than the historical average con-

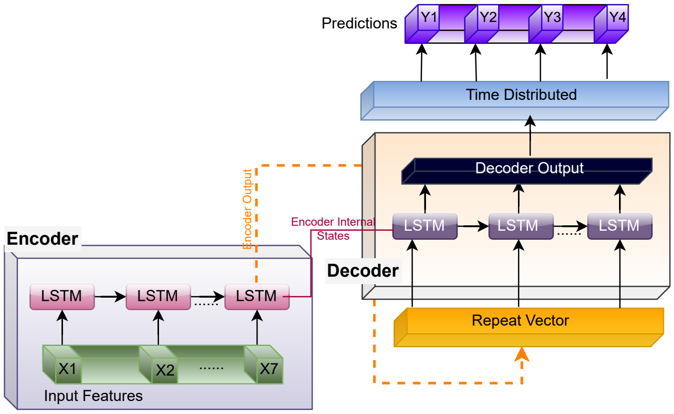


Fig. 2. Sequence-to-Sequence Autoencoder Structure

sumption of the same appliance over the past years during the same hour, month, and weekday of the forecast, as shown in equation 1 where (P) stands for Predicted Power Consumption and (H) stands for Historical Power Consumption, the controller will send an alert to the smart-meter connected to that appliance to control the power consumption to the historical average pattern limit.

$$P_{(h,m,wd)} > \frac{1}{n}\sum_{y=1}^{y=n} H_{(h,m,wd,y)} \tag{1}$$

Where h = hour, m = month, wd = weekday, and y = year.

The system controller was built using the Python programming language and the Pandas library due to its speed in data manipulation tasks and its efficiency in processing large data.

D. Centralized IoB System

In order to evaluate the efficiency of the proposed framework, the distributed IoB system will be compared to the centralized IoB system proposed in [3] through their predictive models. Due to the limitations of the centralized IoB model structure in addressing sequencing-to-sequencing problems as it performs poorly on such tasks, multiple models have been designed to handle each output. That is, four models were built with the proposed centralized model structure to predict the following values individually: Global active power, sub-metering 1, sub-metering 2, and-metering 3. Each model was built using Keras library with an LSTM layer and a Dense layer. The models were run for 20 training epochs with a "mean_squared_error" loss function and "adam" optimization function.

V. Evaluation and Results

This section evaluates the comparison between a distributed IoB system and a centralized IoB system by their prediction model performance, error rates, the accuracy of systems alerts, and the total amount of energy saved resulted from influencing IoT behavior.

A. Model Performance: Loss Function

During the model building process, the model was repeatedly evaluated using the loss function as an essential part of the optimization problem. It is used to estimate the loss of the model so that the weights of the model can be updated to minimize the loss of the next run. Mean squared error was used as a loss function for the developed model. It calculates the mean squared differences between the expected and actual values.

Line plots in Figure 3 illustrate the mean squared error loss over training epochs for the scaled values of training and testing datasets for the distributed model and each centralized model with different outputs.

In Figure 3(a), the distributed model converged reasonably well and both the training and testing loss over the epochs decreased by very close values indicating the good performance of the model. Figures 3(b), 3(c), and 3(d) show the loss performance of three centralized models with outputs: Global active power, sub metering 1, and sub metering 2, respectively. The global active power centralized model loss showed acceptable convergence, while sub metering 1, and sub metering 2 suffered from underfitting as the training loss and the test loss showed a significant difference implying that the models generalized poorly to the testing data. Figure 3(e) illustrates the loss performance of the sub metering 3 centralized model. Clearly, the model suffered from an overfitting issue as the testing loss is higher than the training one.

B. Forecast Error

This subsection will evaluate the mean squared error and mean absolute error for the predictions of testing data in true values scale. These errors will assess the difference between the true value and its predicted value as shown in equation 2.

$$Error_t = Y_t - \hat{Y}_t \tag{2}$$

Where Y_t = true value sample and $\hat{Y}_t$ = forecast value sample.

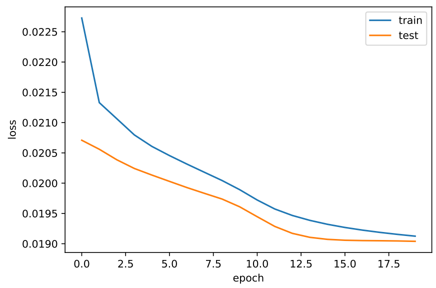
Root mean square error (RMSE) is used to calculate the square root of the mean squared differences between the expected and actual values. As shown in equation 3, it squares each error to make the values positive and then takes the square root of the mean squared error of all values to calculate the error in the original unit which will result in predicting the mean.

$$RMSE = \sqrt{\frac{\sum Error_t^2}{n}} \tag{3}$$

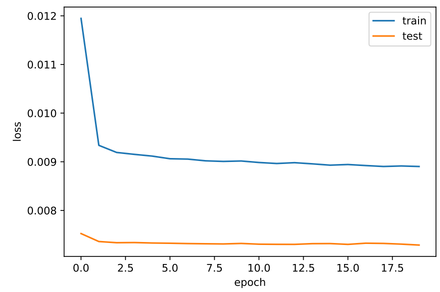
Mean absolute error (MAE) is used to calculate the mean of the absolute differences between the expected and actual values. As shown in equation 4, it takes the mean magnitude of error values regardless of their directions, it will result in predicting the median.

$$MAE = \frac{1}{n}\sum |Error_t| \tag{4}$$

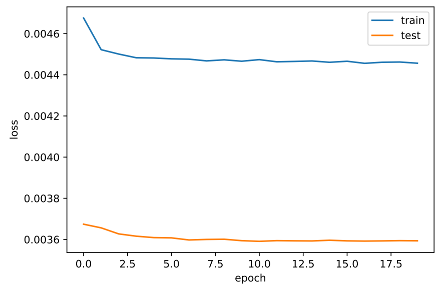
Figure 4 show the RMSE and MAE for the non-scaled testing dataset values for the distributed model and each



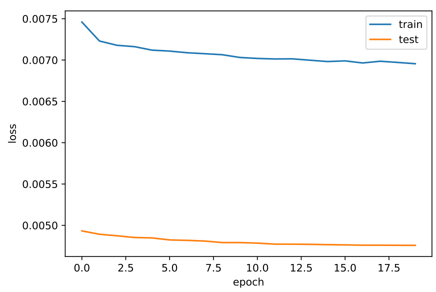
(a) Distributed Model



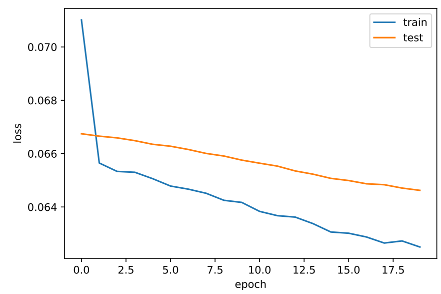
(b) Centralized Global Active power Model



(c) Centralized Sub Metering 1 Model



(d) Centralized Sub Metering 2 Model



(e) Centralized Sub Metering 3 Model

Fig. 3. Models' Loss Performance

centralized model with different outputs. As shown, figures 4(a) and 4(d), the centralized models achieved higher RMSE and MAE values compared to the decentralized model RMSE and MAE for the global active power, sub metering 1, and sub metering 3 outputs. Whereas for the forecast errors of sub metering 1 and 2 values, the decentralized model achieved a slightly higher error compared to the forecast errors of the centralized model, as shown in Figure 4(b) and 4(c).

C. System Alerts

According to Equation 1 for system controller alerts, the system controller will send alerts every time an over-consumption behavior is predicted by the AI model.

Figure 5 shows the total count of alerts sent by the distributed model and each centralized model for each output over 500 hours period. In all centralized sub-meters models except for the centralized sub meter 2 model, the centralized systems send more alerts compared to the distributed system. This happened because the distributed model was more accurate in forecasting with lower forecast errors.

D. Total Saved Power

Based on system alerts, the power consumption of each appliance will be reduced to a historical average limit in case the AI model predicts an excessive consumption. Therefore, the reduction amount per sub meter was calculated from the testing data of 500 hours for distributed and centralized models to test the efficacy of the proposed framework.

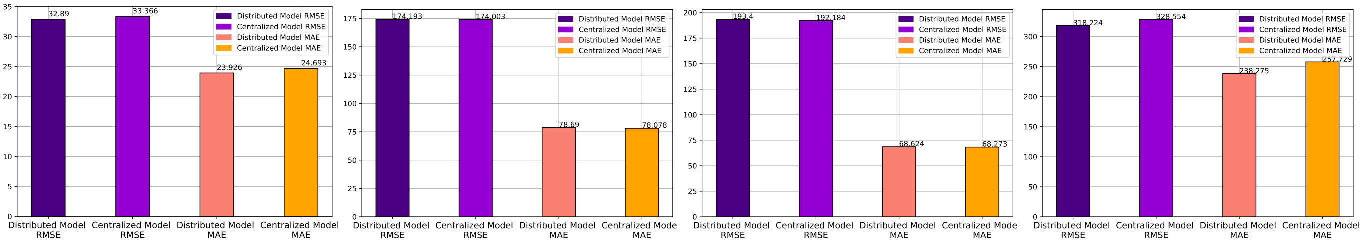
Figure 6 illustrates the total amount of saved power in watt-hour for each sub meter and the global active power for the distributed system and each centralized system. The saved power amount in both system types was almost the same for the global active power and sub metering 2 although the sent alerts were lower in the centralized system for sub metering 2. Whereas for sub metering 1 and sub metering 3, the distributed system saved more power amount than the centralized model with fewer sent alerts, this is due to the accuracy in the prediction model.

In summary, the distributed system model has better performance than the centralized system model as it rapidly converges to the training and testing loss. Moreover, in the RMSE and MAE forecast errors, the distributed system model performed better with lower error values on most of the comparable outputs. Furthermore, although the distributed system sends fewer alerts than the centralized system, the distributed system saved more power for two sub-meters, due to the lower forecast errors of the prediction model.

VI. Conclusion

Aiming at achieving energy sustainability through IoB technology that influences IoT behavior to reach certain outcomes, this paper introduces a novel decentralized IoB framework for household electrical power consumption. Moreover, it presents an experimental implementation of the proposed decentralized IoB framework and a comprehensive evaluation by comparison with a centralized IoB system. The results demonstrate that the decentralized IoB system performs better in terms of prediction accuracy thus sending less alerts by 3.5% and saving more power by 3.4% for 3 sub-meters compared to the centralized system.

In the future, we will investigate the following open issues:



(a) Global Active Power Error (b) Sub Metering 1 Error (c) Sub Metering 2 Error (d) Sub Metering 3 Error

Fig. 4. RMSE and MAE Forecast Errors

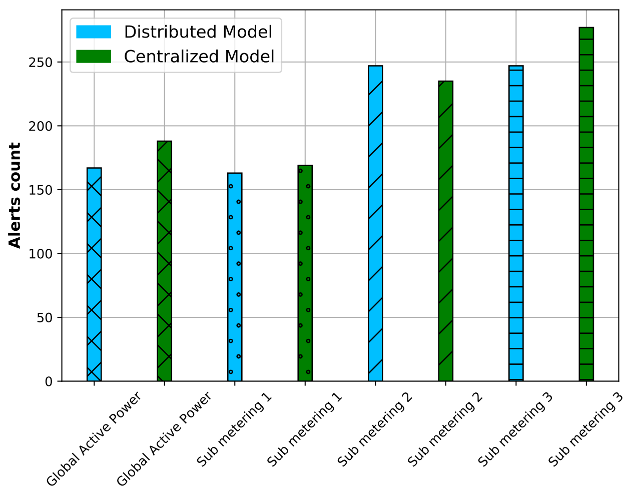


Fig. 5. Alert Count

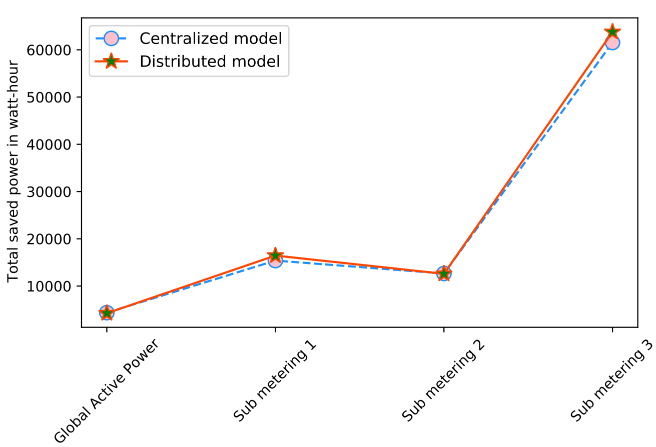


Fig. 6. Total Saved Power in Watt-Hour

- Evaluate the network efficiency on a larger number of connected devices.
- Evaluate the prediction model architecture on a larger number of input features.
- Integrate different decentralization-support techniques such as federated learning and fog computing

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REFERENCES

[1] "Iot market global forecast," https://www.marketwatch.com/press-release/, accessed: 11-11-2021.

[2] "Cisco annual internet report (2018–2023) white paper," https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.html, accessed: 15-6-2021.

[3] H. Elayan, M. Aloqaily, and M. Guizani, "Internet of behavior (iob) and explainable ai systems for influencing iot behavior," arXiv preprint arXiv:2109.07239, 2021.

[4] S. Stack and I. R. Rockett, "Social distancing predicts suicide rates: Analysis of the 1918 flu pandemic in 43 large cities, research note," Suicide and Life-Threatening Behavior, 2021.

[5] "The price for not wearing masks: Perhaps 130,000 lives," https://www.nytimes.com/2020/10/23/health/covid-deaths.html, accessed: 15-6-2021.

[6] I. C.-. forecasting team, "Modeling covid-19 scenarios for the united states," Nature medicine, 2020.

[7] "Face-mask recognition has arrived—for better or worse," https://www.nationalgeographic.com/science/article/face-mask-recognition-has-arrived-for-coronavirus-better-or-worse-cvd, accessed: 15-6-2021.

[8] "In coronavirus fight, china gives citizens a color code, with red flags," https://www.nytimes.com/2020/03/01/business/china-coronavirus-surveillance.html, accessed: 15-6-2021.

[9] "How uber uses psychological tricks to push its drivers' buttons," https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html, accessed: 15-6-2021.

[10] S.-H. Kim, C. Lee, and C.-H. Youn, "An accelerated edge cloud system for energy data stream processing based on adaptive incremental deep learning scheme," IEEE Access, vol. 8, pp. 195 341–195 358, 2020.

[11] D. Syed, H. Abu-Rub, A. Ghrayeb, and S. S. Refaat, "Household-level energy forecasting in smart buildings using a novel hybrid deep learning model," IEEE Access, vol. 9, pp. 33 498–33 511, 2021.

[12] Y. Liu, D. Zhang, and H. B. Gooi, "Optimization strategy based on deep reinforcement learning for home energy management," CSEE Journal of Power and Energy Systems, vol. 6, no. 3, pp. 572–582, 2020.

[13] H.-M. Chung, S. Maharjan, Y. Zhang, and F. Eliassen, "Distributed deep reinforcement learning for intelligent load scheduling in residential smart grids," IEEE Transactions on Industrial Informatics, vol. 17, no. 4, pp. 2752–2763, 2020.

[14] "Individual household electric power consumption data set," https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption, accessed: 11-11-2021.