AuGrid: Edge-Enabled Distributed Load Management for Smart Grid Service Providers

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***Abstract*—In this paper, we propose and design AuGrid, an LSTM-based model for geographically aware smart grid service providers, which predicts the hourly load requests from users. We also develop a pricing model which depends on the predictions obtained from AuGrid for deciding per unit cost of energy in contrast to the existing schemes that focused solely on the load requests. The crux of this work is that the suppliers may plan better with forecasts than being in uncertainty. Since smart grids are well connected, logically neighboring smart grids may exchange information and energy on the requirement. We train AuGrid with a lookback set to 2 using real-world datasets and demonstrate its robustness by predicting the load requests for different suppliers. We propose deploying the AuGrid system on geographically aware suppliers for facilitating intelligence on the edge while reducing the user sample space and increasing data security. On extensive implementation and deployment, we observe that AuGrid offers minuscule loss (below 0.1) and the pricing model offers a reduction in per-unit cost by almost 75% in comparison to existing solutions. Additionally, AuGrid requires 30% CPU and 40% RAM of single processor boards on deployment, which illustrates its suitability for resource-constrained devices.**

***Index Terms*—LSTM, edge intelligence, smart grid, machine learning, Internet of Things.**

I. Introduction

Smart grids are green infrastructures for the suppliers to strategically serve electricity/energy/power requests from users/consumers with promising results. However, the load requests and their patterns over the years have observable changes due to the COVID-19 pandemic [1], which necessitates the need for novel solutions for flattening the generation-consumption curve. Profiling consumers is a common practice in smart grids for efficient management, which requires the processing of sizeable data. Edge processing-based network architectures may be a suitable solution. However, the use of smart meter data for profiling users like the number of consumers in the household, electrical appliances, and usage patterns is concerning due to potential privacy and security threats. Such issues may be overcome by making the profiling at the geographically aware suppliers/marketplaces based on load requests from its customers as a community, instead of making it user/household-specific. The per-unit cost of energy, which particularly depends on load requests, is also a concerning factor.

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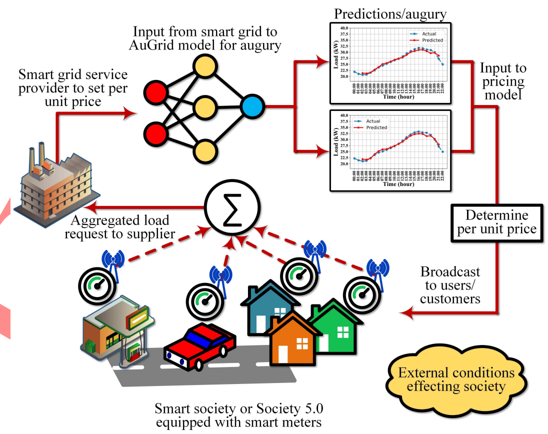


Figure 1: Overview of the proposed AuGrid system.

In this work, we propose AuGrid as a method for forecasting the load requests from the consumers on an hourly basis every month at the supplier end. The Au in AuGrid represents Augury (or forecast) and Grid represents smart grids. As shown in Fig. 1, we consider geographically aware suppliers offering their services to a set of users. These users are a part of an IoT-enabled environment and equipped with smart meters. We develop a model for enabling a supplier to predict the local aggregated hourly load requests from these users. We achieve this by using a long short-term memory (LSTM)-based recurrent neural network (RNN) for predicting the load requests. The LSTM helps in making the predictions by considering the previous load requests as the energy consumption increments or decrements in proportion to the previous load. We also develop a dynamic pricing scheme to regulate and manage the energy supply by considering how far off the predictions are from the actual requests. In summary, AuGrid enables suppliers to forecast the load requests and set the per-unit cost according to the predictions, in contrast to depending solely on load requests and energy generation [2].

A. Motivation

Energy conservation and the use of renewable sources are the need of the hour. Towards this, existing literature offers multiple solutions for profiling consumers for serving their load requests. Moreover, some of the solutions also focus on studying the consumption by single appliances such as air conditioners, refrigerators, and other similar devices. These methods raise privacy concerns, which mandates the need for secured and reliable solutions. Also, pricing models that solely depend on load requests and energy generation do not help in making informed decisions due to the uncertainty of the future. Such challenges motivate us in developing the proposed AuGrid system of predicting the community load profiles from the supplier's perspective based on the previous requests and setting the per-unit cost accordingly. It does not need user profiling on an individual level. Adaptive pricing models help in regulating the consumption by users.

B. Contribution

We develop AuGrid as a system for smart grid service providers for forecasting load requests and setting the per-unit costs without raising privacy concerns. The specific set of contributions are:

- ***Load Profile:*** We profile the load requests as a community rather than as an individual. This method requires the total request data at the suppliers rather than individual smart meters.
- ***Hourly Predictions:*** We develop an LSTM-based model for making hourly predictions, which helps the suppliers in making cost, generation, and conservation decisions.
- ***Adaptive Pricing Model:*** We develop a pricing model for setting the cost per unit energy based on the predictions from AuGrid and the actual load request.
- ***Edge Intelligence:*** We develop AuGrid as a system for geographically aware service providers. They make the predictions according to the set of their customers, which reduces the sample space and also increases data privacy.
- ***Evaluation:*** Through extensive experiments on a real dataset, we demonstrate the efficiency of Augrid in comparison to existing solutions.

It may be noted that we focus on predicting the load requests and their corresponding price in this work and refrain from modeling the communications among the smart meters or the edge. However, green methods such as in [3] are promising solutions for reducing consumption due to communications.

We organize the rest of the paper as follows. We present some of the relevant existing literature in Section II. We then present a background on LSTM in Section III and elaborate on the dataset (used in this work) in Section IV. We then illustrate the AuGrid system in Section V and present the network architecture along with the proposed pricing model in Section VI. We then present our observations in Section VII and finally conclude in Section VIII.

II. Related Work

A. Smart Grid and Applications

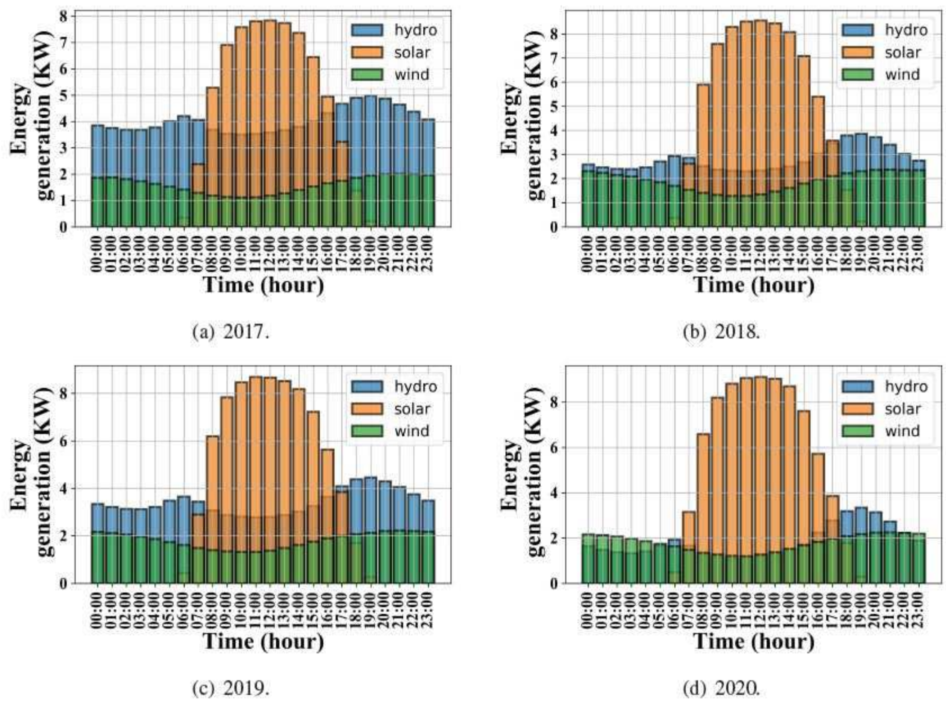
Forecasting power consumption in smart grids is beneficial for both customers and service providers. The authors in [4] focused on air conditions and proposed an ARIMA-based model to predict the energy consumption for the next day. However, methods on the overall electricity consumption help in making better decisions over those from the selective ones. Alazab *et al.* [5] accounted for the electricity production, consumption, and price elasticity to predict the stability of a smart grid system. They used a multi-dimensional LSTM to achieve this. The authors in [6] profiled the energy usage according to the user profiles and proposed an auction-based mechanism for optimizing the energy trade between the user and supplier. They relied on the Anderson model for profiling the consumers. In contrast to provisioning and consuming energy, the authors in [7] proposed a Lyapunov optimization framework for virtualized energy storage. The consumers are oblivious to the pooled infrastructure and other proceedings. However, although stated as an advantage by the authors, their work only considers the current system state and does not predict the outcomes of the future. In our opinion, some sight into the future helps in making better decisions, especially when dealing with renewable sources. Other possible energy harvesting schemes in smart grid-powered wireless networks may be found in the work by Hu *et al.* [8].

B. Energy Management in Smart Grids

Forecasting energy requirements leads to better energy management in smart grids. Latifi *et al.* [9] highlighted the need for flattening the curve between generation and consumption rates. The authors in [10] proposed a data mining method for profiling the energy consumption in households from the data in smart meters. Liang *et al.* [11] also took a similar data-driven consumer-centric approach. While such methods prove beneficial, it also raises data privacy concerns and the consumers might not be willing to share the necessary details. Hassan *et al.* [12] on the other hand, proposed a Markov chain-based method, which considers the energy usage scheme, randomness of energy requests, and the current state for making management decisions. They considered a cellular network setup, which interacts with renewable source powered smart grids, and they communicate with one another for reacting to the dynamic usage policies. Further, the authors in [13] designed a smart grid-based simulator for studying, developing, and testing energy management schemes.

C. Security in Smart Grids

The studies of forecasting the loads are also important to identify attacks in smart grids. One of the common attacks is load redistribution, where the attackers inject load across different buses, without exceeding the total production. Kavyani and Hedman [14] proposed a fast greedy algorithm to detect such attacks. Islanding is another challenge where the energy-supplying devices keep dissipating even when the consuming device is inactive. Kumar and Bhowmik [15] designed a hidden Markov model-based method for detecting such attacks with minimum latency. Due to automation and network adoptions, smart grids are open to cyber attacks [16]. Some services are also outsourced to third parties for operational simplicity, which raises privacy concerns. Xue *et al.* [17] identified such



(a) 2017. (b) 2018. (c) 2019. (d) 2020.

Figure 2: Power generation from renewable sources.

issues and developed a privacy-preserving scheme for secured outsourcing and dynamic pricing predictions.

D. Pricing Models in Smart Grids

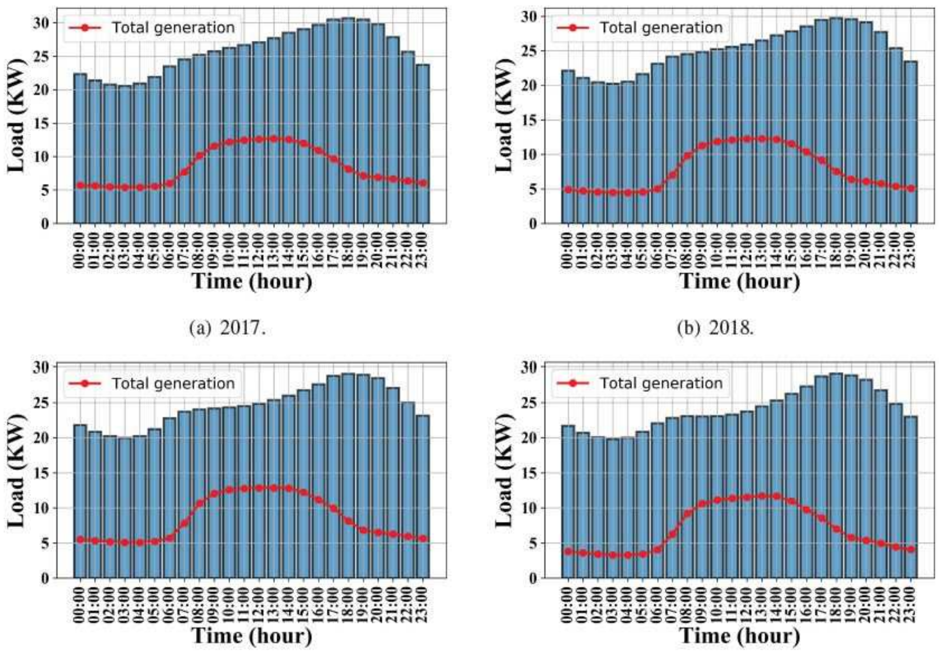
Yang *et al.* [18] proposed a classification model for identifying the category of users based on their consumption profile and device ownership before determining the price according to the load request. While such methods are promising and efficient, they open the scope for security threats and privacy breaches. The authors in [19] highlighted such threats (hidden electricity thefts) and also pointed out the vulnerabilities in smart grids. On the other hand, Almahmoud *et al.* [20] proposed a threshold-based policy for determining the price of energy. To overcome the management challenges of smart grids, Wei *et al.* [21] proposed using an intermediate entity between the suppliers and consumers for easy energy trading.

E. Synthesis

We observed that researchers have been developing methods for flattening the generation-consumption curve. These works focus on forecasting the load requests (monthly) for enabling the service providers to be well prepared. Additionally, some authors have presented methods for profiling the customers and their energy usage, along with the equipment they use. This allows strategic energy harvesting (both centralized and decentralized). Further, we observed different versions of pricing models consisting of varying parameters, which help in optimizing the customer and service provider incentives, so that both parties are satisfied. Although these approaches are interesting and they have merit, some challenges persist consistently. These include potential security threats and privacy concerns. A granular (hourly) prediction of the load requests, without the need for profiling each customer has two-fold advantages. It reduces 1. privacy breaches and 2. maintains consistent price for a community as a whole. Further, notable deviations of the consumption from the predictions may be addressed as a concern by the authorities. Also, in the case of deviations in the actual trend, the proposed Augrid method dynamically modifies the cost of per unit energy, in contrast to monthly prices, which otherwise may lead to unplanned energy consumption, and eventually decrease the supplier's incentive.

III. Bias and Background on LSTM

Conventional neural networks are incapable of exploiting past observations (experience) and decisions. While recurrent neural networks (RNNs) overcome this issue, they cannot depend on states that are beyond the recent past. LSTMs are special RNNs that overcome such challenges with additional gates and their features. In the first step, in the forget gate layer, on receiving a new input, it first decides on the content that needs to be forgotten. It uses a sigmoid function (values between 0 and 1) to achieve this. It then uses its input gate layer (another sigmoid function) for extracting the necessary information from the new input and a $\tanh$ layer (values between -1 and 1) to create a new vector representation of the new input. It combines the two before adding to the previous cell state from the forget gate layer. The LSTM then outputs its results which is again a filtered version from a combination of sigmoid and $\tanh$ functions (similar to the input gate layer). In this work, we use the LSTM to keep track of the previous



(a) 2017.

(b) 2018.

(c) 2019.

(d) 2020.

Figure 3: Load (bars) versus total renewable power (line).

2 observations. In the subsequent section, we first discuss the dataset in this work and then present our training results.

IV. Dataset

We use the COVID-EMDA+ dataset [1], which consists of data corresponding to the electricity market, public health, weather, mobile device location, and a light satellite at night of some of the typical cities in the United States from existing marketplaces. The authors developed this dataset to primarily study the impact of the COVID-19 pandemic on the electricity markets, particularly over the years from 2017 to the present. For realizing this work, among others, we focus on the power generation from renewable sources (hydro, wind, and solar) and load requests.

A. Power Generation

The COVID-EMDA+ dataset contains the energy generation data of different marketplaces, such as CAISO, MISO, ISO-NE, and others using different sources (both renewable and non-renewable). We consider only renewable sources, typically hydro, solar, and wind. Each of the records in Fig. 2 represents the hourly energy generation by each source averaged over the entire year. Please note that the figures represent the data from the CAISO marketplace. We observe that solar and wind power have not changed over the years. However, we observe a decline in the energy from hydro sources (Fig. 2(d)) because the US depends on other energy sources as hydroelectricity has harmful effects on wildlife habitat, water quality, water life, and reduces benefits to rivers. Climate changes also play a significant role in energy generation from renewable sources. We sum each of the hourly averages of energy generation and present them in Fig. 3 (line).

B. Load Profile/Requests

The load profile represents the electricity or energy load on the marketplace from different users/customers. It depends on the user profile, climate, and holiday season. The bars in Fig. 3 depict the averaged hourly load requests on CAISO across different years. We observe that the trend remains the same. The line in each of the figures represents the total generated power by renewable sources in Fig. 2. We infer that the gap between the load and generation is significantly large (almost 67%), which results in the increased dependency on non-renewable power sources. We observe a further increase in the difference between the load and generation in 2020 (Fig. 3(d)). This is due to the reduction in the hydropower in Fig. 2(d). The difference in Fig. 3 strengthens the need for management and administrative solutions as establishing new infrastructures for increasing generation by renewable sources does not happen overnight. We account for the importance of the load profiles and develop a model that predicts the load from the perspective of the supplier.

V. The LSTM-Based AuGrid Model

We take the CAISO load profile from the COVID-EMDA+ dataset and train an LSTM-based model (refer Section III). We average each of the hourly load records across each month, resulting in 24 data points. We use the load data from January 2017 for training our model and use it for predicting the same for the subsequent months and years.

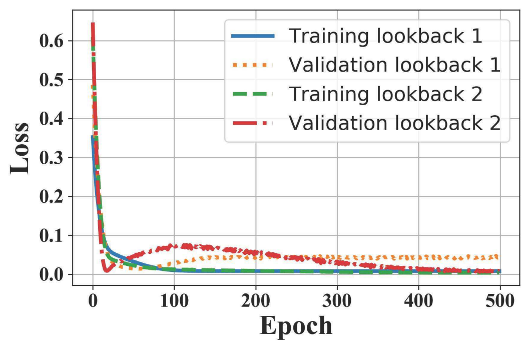


Figure 4: Loss during training and validation.

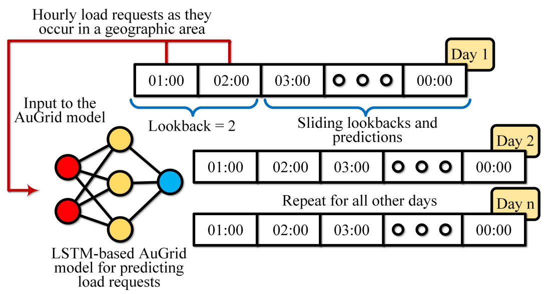


Figure 5: Training the proposed LSTM model.

A. Training the LSTM Model

We use the hourly averaged data in January 2017 from CAISO to train our model. We set the lookback to values greater than 1 to identify the least number of past load profiles necessary for predicting the other monthly sequences. In our opinion, it is beneficial to stochastically quantify predictions on time-series sequences such as load profiles using the loss (mean square errors) rather than accuracy. Fig. 4 represents the loss during the training process. We observe that the training loss for both the lookback values remains the same. However, on validation, the model with lookback value 1 has a loss higher than that in the case of lookback value 2 (refer epoch $400-500$ in Fig. 4). This is because the load profile changes with varying seasons, holidays, electrical appliances, number of consumers, and others, and lookback set to only 1 value is not sufficient to predict the subsequent load sequence. More than 1 previous value is necessary. Interestingly, we observe a loss of almost 0 on the validation data when the lookback value is equal to 2 at 400 epochs, and then the model converges ($400-500$ epochs). It may be noted that, since we obtain convergence, we restrict our representation in Fig. 4 to look back up to 2. It also helps in maintaining the simplicity of representation. Based on this observation, we set the lookback as 2. In summary, we require two load requests to start predicting the rest. For instance, we look at the load requests at $01:00$ and $02:00$ hours (Fig. 5) to predict the ones from $03:00$ hours. We then slide on to the next hourly predictions and repeat the same for all the other days.

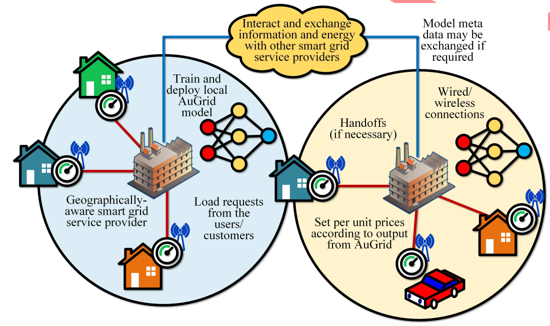


Figure 6: Network architecture.

VI. Network Architecture and Pricing Model

In this section, we present a method for determining the price of supplying each unit of energy from the suppliers. As shown in Fig. 6, we consider a set of x geographically-aware energy suppliers/market places $M = \{m_1, m_2, \ldots, m_x\}$ for a set of y users $U = \{u_1, u_2, \ldots, u_y\}$. Each supplier ($m_a$ for instance) offers its services to a subset of users/customers $u^c_{m_a} \subset U$. We consider $P^{base}_{m_a}$ as the base price per unit for supplier m_a. This value of $P^{base}_{m_a}$ is dependent on the procurement of raw materials, overheads due to energy generation, its storage, and delivery. The base price depends on the supplier and we assume that they strategically set it in compliance to their conditions. We determine the variability on the base price (λ) according to the difference in the actual load request from the users against the outcomes of the LSTM prediction model in Section V-A. For load requests (l_{u_b}) from user u_b, we calculate the total load request on m_a as $L_{m_a}(t) = \sum_{i=1}^{y} l_{u_b}(t)$. For predictions $\mathcal{P}_{m_a}$ for m_a, we set the value of λ according to the following conditions:

$$\lambda_{m_a}(t) = \begin{cases} L_{m_a}(t) - \mathcal{P}_{m_a}(t), & \text{if } > 0 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Since the load request varies with each hour of the month, we formulate the per-unit price as a function of time t. We consider $P^s_{m_a}(t)$ as the selling price per unit for a supplier m_a and calculate it as:

$$P^s_{m_a}(t) = P^{base}_{m_a} + \alpha^s_{m_a} \times (tan^{-1}(e^{\lambda_{m_a}(t)}) + \epsilon) \tag{2}$$

where $\alpha^s_{m_a}$ is an arbitrary constant for the supplier m_a for setting the rate of increase or decrease of $P^s_{m_a}(t)$ and ϵ is some positive constant (useful when $e^{\lambda_{m_a}} = 0$). Since we consider a smart grids with multiple suppliers, we do not rule out the possibility of borrowing energy from one another in the case of surplus demand. Inspired from the work of [22], we formulate the borrowing price as a quadratic cost function in terms of the demand. Mathematically, for a demand from m_b (d_{m_b}), we calculate the borrowing price by m_a ($P^{br}_{m_a}$) as:

$$P^{br}_{m_a}(t) = P^{base}_{m_a} + \alpha^{br}_{m_a} \times [a(d_{m_b})^2 + b(d_{m_b}) + c] \tag{3}$$

where $\alpha^{br}_{m_a}$ and its purpose is similar to that of $\alpha^{s}_{m_a}$ in Equation 2 and a, b, and c are positive constants.

Theorem 1. *The selling price ($P^s_{m_a}(t)$) in Equation 2 is convergent.* □

Proof. We prove that the proposed $P^s_{m_a}(t)$ is convergent by solving $\lim_{t\to\infty} P^s_{m_a}(t)$. Using properties of limits, we modify Equation 2 as:

$$\lim_{t\to\infty} P^s_{m_a}(t) = \lim_{t\to\infty} P^{base}_{m_a} + \lim_{t\to\infty} \alpha^s_{m_a}(tan^{-1}(e^{\lambda_{m_a}(t)}) + \epsilon) \tag{4}$$

The first term in Equation 4 is a constant which results to $P^{base}_{m_a}$. On the other hand, we remove the constants from the second term and solve $\lim_{t\to\infty} tan^{-1}(e^{\lambda_{m_a}(t)})$. The function e^x has a range of $[0, \infty)$ and $tan^{-1}(x)$ has a range of $[-\pi/2, \pi/2]$. Since we consider only positive values, $tan^{-1}(x)$ has a range of $[0, \pi/2]$ and $[0, \infty) \cap [0, \pi/2] = [0, \pi/2]$, implying:

$$\lim_{t\to\infty} P^s_{m_a}(t) = P^{base}_{m_a} + \frac{\pi}{2} \tag{5}$$

which is a positive constant. We conclude that the proposed per unit price in Equation 2 is convergent. □

Algorithm 1: AuGrid predictions and cost of per unit energy.

Input: $L_{m_a}(t-2)$ and $L_{m_a}(t-1)$

```
// Previous 2 load requests since
lookback = 2
```

Output: $P^s_{m_a}(t)$

```
// Cost of per unit energy
```

1 Predict $L_{m_a}(t)$ using the trained AuGrid model

```
// Input Lma(t-2) and Lma(t-1)
```

2 Calculate λ_{m_a} according to Equation 1

```
// Difference between predicted and
actual load request
```

3 Calculate $P^s_{m_a}(t)$ according to Equation 2

4 Broadcast to concerned users

Assumption and Future Work: In this work, we make the following set of realistic assumptions:

- We consider a fixed set of users under each supplier and refrain from considering user mobility and handoffs. In this work, we focus only on making predictions on load requests.
- We consider that all users under each supplier pay the same price.

In the future, we plan to extend this work by considering the heterogeneity of the user demands and determining the per unit energy costs accordingly. These factors may be reflected on a parameter β, such that price for a user u_b is $P^{cost}_{u_b}(t) = \beta^{m_a}_{u_b}(P^s_{m_a}(t-1) - P^s_{m_a}(t)) + P^{base}_{m_a}$.

In summary, the proposed AuGrid system works according to Algorithm 1. We take the previous two aggregated load requests ($L_{m_a}(t-2)$ and $L_{m_a}(t-1)$) and use them as inputs to the LSTM model (Step 1). We then calculate the difference between the predictions and the actual load requests (Step 2) and calculate the cost of per unit energy according to Equation 2 (Step 3). Finally, we broadcast it to the users (Step 4). Asymptotically, Algorithm 1 (AuGrid) takes $\mathcal{O}(1)$ time for generating its results in each iteration.

Table I: Hardware metrics (averaged) on training and deploying AuGrid.

	i5 PC (laptop)	**Single processor board**
Training time	48.442s	186.694 s
Prediction time	1.68 s	26.40 s
Model size	30 KB	25 KB
CPU usage (train)	66.21%	30.24%
RAM usage (train)	71.99%	34.61%
CPU usage (prediction)	31.71%	26.03%
RAM usage (prediction)	67.14%	40.36%

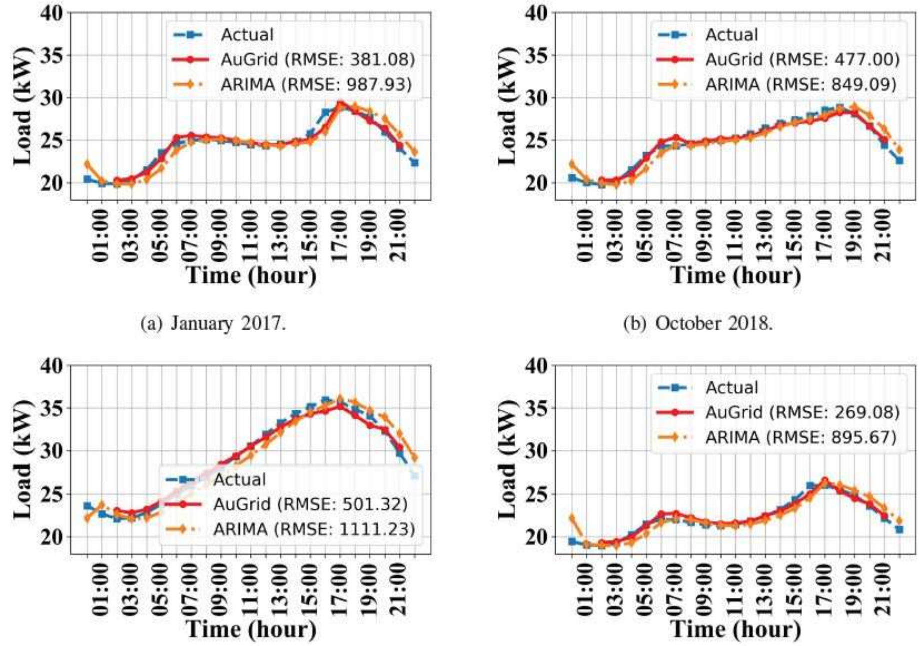
VII. Performance Evaluation

In this section, we present our observations from the experiments on AuGrid using the dataset mentioned in Section IV and the pricing model in Section VI. Towards the implementation of this work, we use an i5 personal computer laptop (Dell Inspiron) as well as a resource-constrained single processor board (Raspberry Pi 3B+). We select these devices to demonstrate the feasibility of implementing AuGrid on resource-rich as well as resource-constrained devices and use Python 3.7 for both devices.

A. Resource Consumption

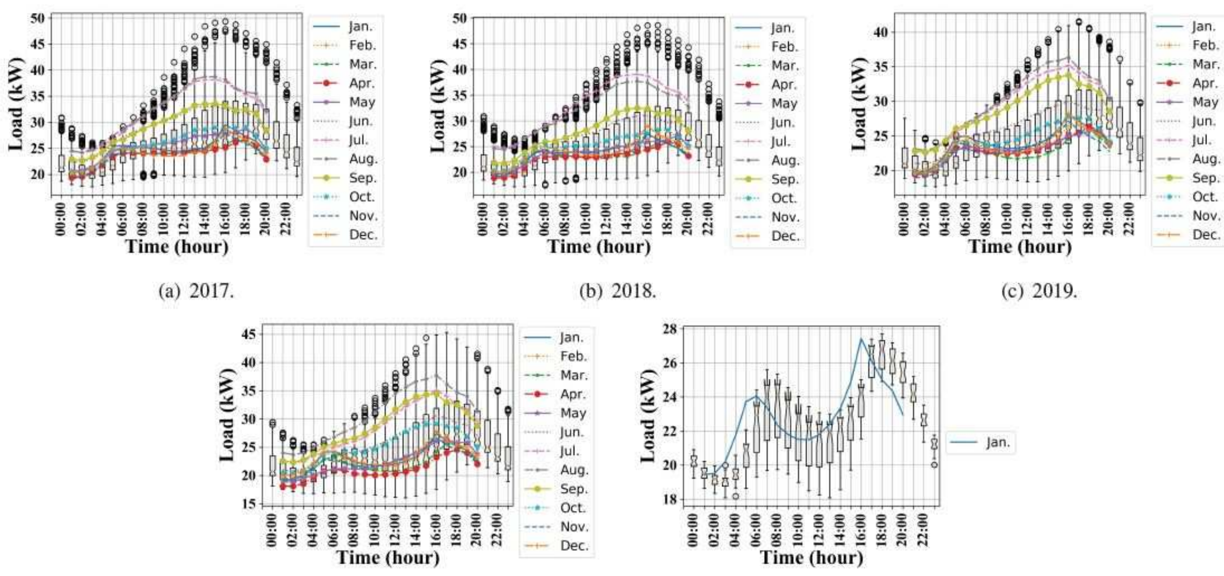
We train and deploy the models in both the category of devices. We present our observations (averaged) on executing our experiments multiple times in Table I. As expected, we observe a higher training time (187 s) in the case of the single processor board in comparison to that in the case of PC (49 s). This is because of the lower clock cycles. Due to the same reason, on average, while the PC takes 1.67 s for predicting the load request sequence, the single processor board takes 26.40 s. However, the increased delay does not affect the performance of the AuGrid system as it is not a hard real-time task and such delay ranges are tolerable. On the other hand, we observe that the PC requires 66.21% CPU for training and 31.71% for predicting, which is almost 30% more than the resource-constrained device. This is because the PC executes multiple other processes in the background in contrast to single processor boards. This is the reason why we observe similar patterns in the case of RAM usage.

We infer from our observations that the proposed AuGrid system is feasible for deployment (both training and making



(a) January 2017. (b) October 2018. (c) July 2019. (d) November 2020.

Figure 7: Comparison of training (on Jan. 2017 data) and validation predictions across different months and years for CAISO using AuGrid (LSTM) and ARIMA.



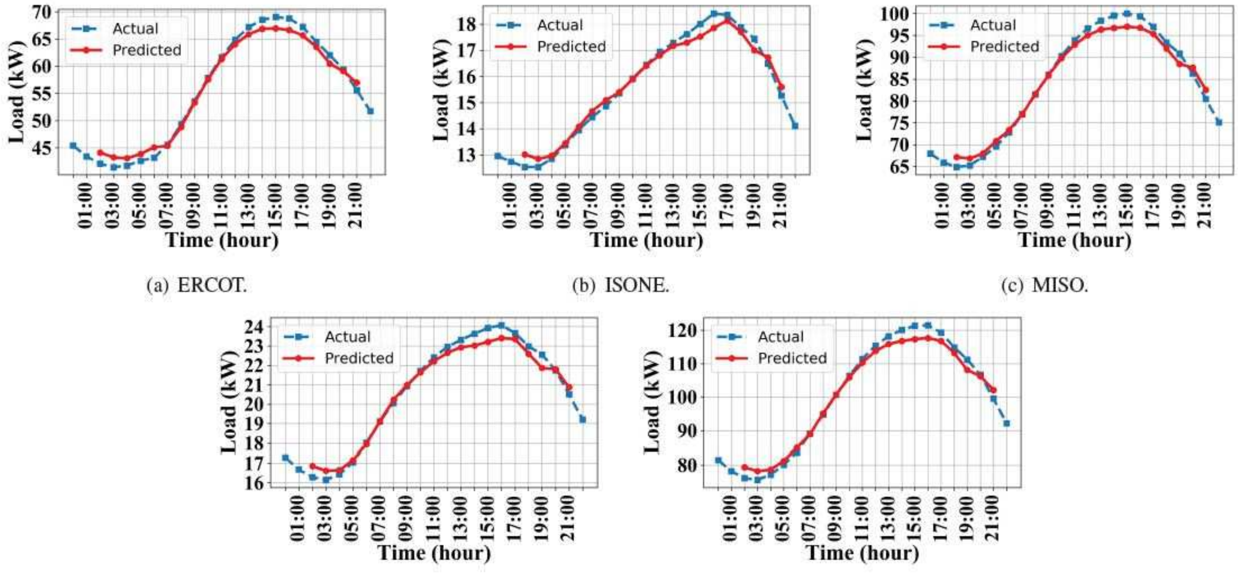
(a) 2017. (b) 2018. (c) 2019. (d) 2020. (e) 2021

Figure 8: Predictions from the proposed LSTM model for CAISO marketplace.

predictions) in both resource-rich and resource-constrained devices with ease. Its suitability on resource-constrained devices implicitly dictates low-cost adoption on legacy systems.

B. Predictions from AuGrid

As mentioned earlier, we train the model on the load data in January from CAISO. Fig. 7 depicts the predictions. We observe that the predictions fit almost perfectly on the training data (Fig. 7(a)), conforming to our observations in Fig. 4. We arbitrarily choose one month from each year (2018 – 2020) for representing our observations on making predictions on the unseen data. In each case (Figs. 7(b) to 7(d)), we observe that the predictions fit almost perfectly, irrespective of the month, year, season, and other possible dependencies. It may be noted that there are no predictions for 00:00 and 01:00 hours. This is because the trained model needs two data points for making the predictions. Further, we refrain from finding predictions



(a) ERCOT. (b) ISONE. (c) MISO. (d) NYISO. (e) PJM.

Figure 9: Predictions from the proposed LSTM model for different marketplaces apart from CAISO.

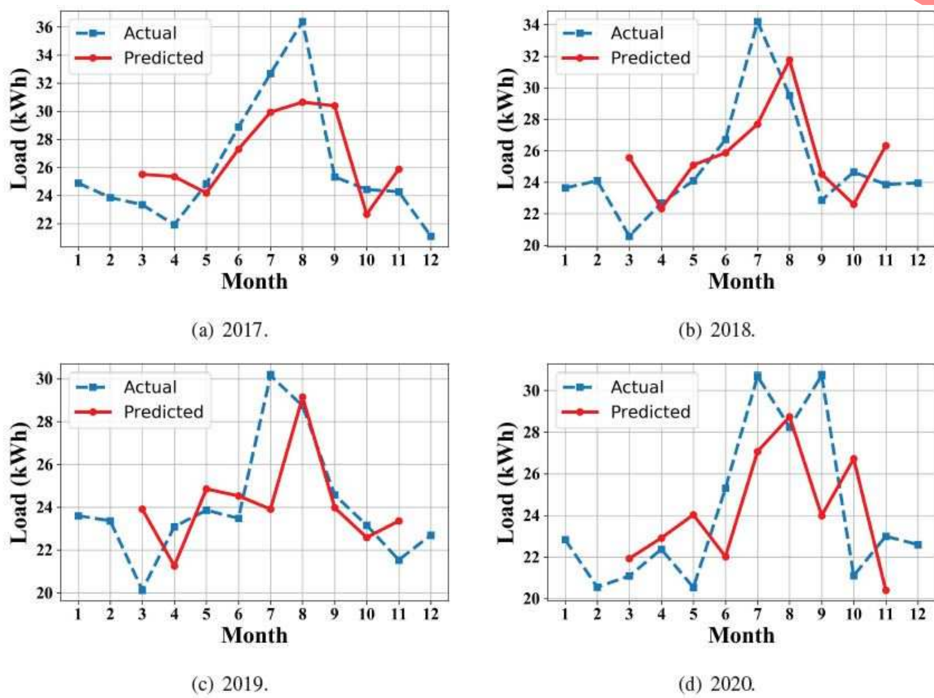
at 22:00 and 23:00 hours after obtaining the declining trend (point of inflection) at 17:00 or 18:00 hours. Another popular method for forecasting data sequences is the Auto-Regressive Integrated Moving Average (ARIMA) model. In contrast to LSTMs, it does not depend on neural networks and the gates mentioned in Section III. Instead, it depends on a statistical analysis of the data using regressions, integrations, and moving averages (as the name suggests). The autoregression helps in regressing the lagged and prior values. The integration differences and helps in converting the non-stationary data to stationary. Finally, the moving average helps in smoothing the results as a result of the difference between the lagged observations and residual errors. Typically, ARIMA models are useful for non-stationary data, which is not the case of the scenario considered in this work. Figure 7 contains the root mean square error for both AuGrid and ARIMA. We observe consistently high RMSE values (almost 500 units) for ARIMA throughout all the cases. We account for the mentioned conditions and consider the LSTM-based forecasting method. Finally, using Fig. 7, we establish the efficiency of the proposed model and present its predictions for all months across 2017−2021 in Fig. 8. The box plots represent the actual distribution of the load profiles in the COVID-EMDA+ dataset along with the outliers. Since the developed model generates the actual load profiles efficiently, predictions like those in Fig. 8 (for CAISO) may be used to study the possible requests at the marketplaces. To further demonstrate the effectiveness of the proposed model, we arbitrarily present its predictions on August 2020 for marketplaces apart from CAISO (Fig. 9). Interestingly, we observe that although we train the model on data from CAISO, it predicts those for other marketplaces with high precision. We attribute this behavior to the nature of load consumption as its pattern does not change. We infer that the developed model is suitable across marketplaces and suppliers.

Additionally, we train another LSTM using the same lookback value as earlier and use it to predict the monthly load request in the CAISO. Fig. 10 depicts the predictions of the load request for each month over the years. We observe that the model is incapable of making these predictions as efficiently as those in Fig. 8. We observe relatively better predictions for the years 2018 (Fig. 10(b)) and 2019 (Fig. 10(c)). On the other hand, we observe incorrect predictions in the case of 2017 (Fig. 10(a)) and 2020 (Fig. 10(d)). We attribute this undesired increase of the mean square error to the low number of training data points (only 12). We infer that additional tuning is necessary to help the model for predicting the monthly load requests. We plan to address this issue in our extended work.

C. Benchmark and Comparison

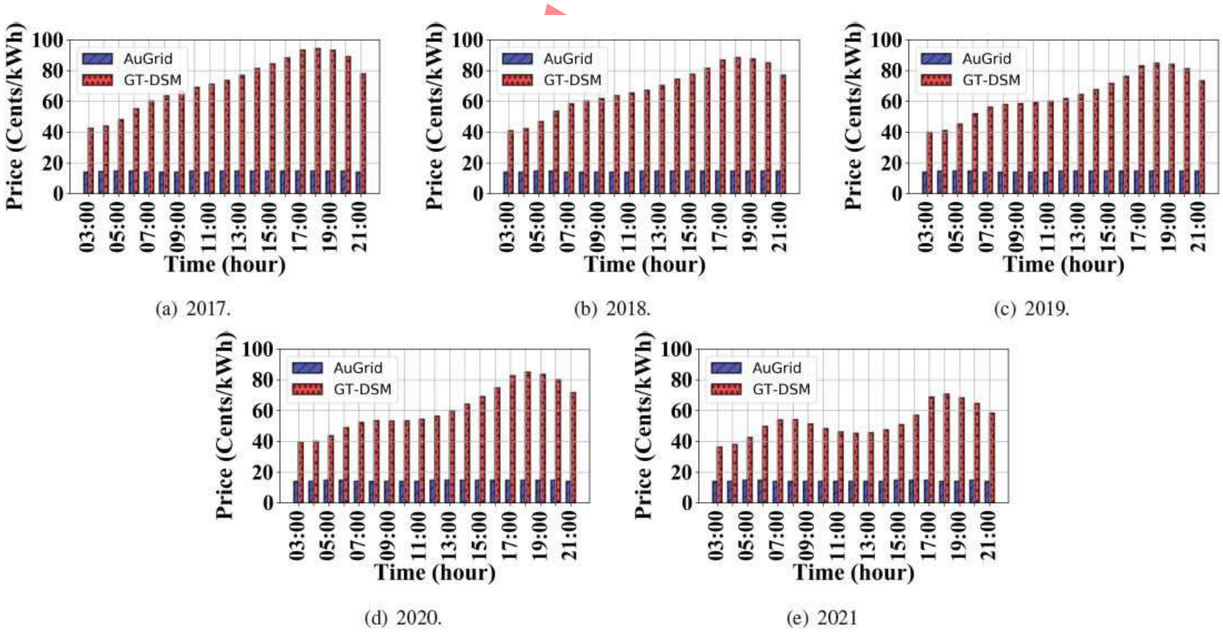
We compare the per unit selling price in Equation 2 and our bias of considering auguries with the works of Saghezchi *et al.* [2]. They proposed a game theory-based solution (GT-DSM) for setting the prices for demand-side management. They formulated the price for per unit energy from the smart grids as a function of the aggregated load requests as $\mathbb{P} = \mathcal{A}L_{agg}^2$ where L_{agg} is the aggregated load request and $\mathcal{A}$ is a pre-defined constant set to 0.1.

Fig. 11 depicts the price per unit energy from the smart grids for each year. We set the price as 13.19 cents per kWh [23]. As expected, we observe that the price set by AuGrid is much less (almost 75%) than that of GT-DSM. This is because they are dependent solely on the hourly load requests in contrast to Augrid, and are more concerned about the difference between the load requests and the predictions (refer Equation 2). We also observe that the fluctuations in load requests (hourly) reflects in the prices set by GT-DSM throughout all years (Figs. 11(a)-11(e)). AuGrid, on the other hand, demonstrates a much



(a) 2017. (b) 2018. (c) 2019. (d) 2020.

Figure 10: Predictions from the predictive model across different years for CAISO.



(a) 2017. (b) 2018. (c) 2019. (d) 2020. (e) 2021

Figure 11: Comparison of price per unit kWh.

stable price for the same load requests, which corroborates with Theorem 1. The low selling price may be a concern for low profits by the marketplaces. To overcome this issue, the Augrid model has a constant value $P^{s}_{m_a}(t)$. The marketplaces may set it according to their convenience and techniques like [24] coupled with the forecasts by Augrid may be used to optimize them. It may be noted that the low prices set by Augrid may not be acceptable by suppliers wanting to make high profits. To overcome this issue, the suppliers may set higher values to $P^{base}_{m_a}$. However, accounting for the pandemic, we maintain parameters that are considerate.

VIII. Conclusion

In this paper, we proposed an LSTM-based load request prediction model (AuGrid) for smart grid service providers with a lookback set to 2. We also formulated a pricing model based on the predictions from AuGrid in contrast to those that solely depend on the load requests and energy generation rates. The results from our experiments show the stability of the proposed model and also corroborates the fact that the service providers offer better load and price when the future is known. We demonstrated the feasibility and robustness of the proposed AuGrid system using real-world datasets. We also presented its implementation and deployment on both resource-rich and resource-constrained devices with minimal hardware consumption. While we observed increased delays in training and making predictions on the single board processors, these delays are tolerable as we make hourly predictions, which need not be real-time

In the future, we plan to extend this work by considering the heterogeneity of the users and setting the individual per-unit prices accordingly. We also plan to further improve AuGrid to offer better monthly predictions.

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