Forecasting Residential Energy Consumption: A Case Study for Greece

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Abstract: Residential energy consumption forecasting has immense value in energy efficiency and sustainability. In the current work we tried to forecast energy consumption on residences in Athens, Greece. As a proof of concept, smart sensors were installed into two residences that recorded energy consumption, as well as indoors environmental variables (humidity and temperature). It should be noted that the data set was collected during the COVID-19 pandemic. Moreover, we integrated weather data from a public weather site. A dashboard was designed to facilitate monitoring of the sensors' data. We addressed various issues related to data quality and then we tried different models to forecast daily energy consumption. In particular, LSTM neural networks, ARIMA, SARIMA, SARIMAX and Facebook (FB) Prophet were tested. Overall SARIMA and FB Prophet had the best performance.

1 INTRODUCTION

Electricity was invented in 1752. Over the years and as technology advanced, electricity evolved from being a commodity mostly enjoyed by the upper class to a service available in every household. But as the population grows and production is heading to a green model, meanwhile energy prices are increasing, which makes someone wonder if having electricity in the future will be once again considered a luxury (Seel et al., 2018). Since the beginning of 2022 and especially since the recent turmoil in Eastern Europe, a rally of increasing prices in energy was registered globally with many European countries being more vulnerable to the current energy crisis. It is easily understood that the energy crisis is not a temporary state but a problem that the whole world needs to address and find innovative ideas to confront it.

To resolve the energy crisis in Europe, many European countries such as Spain, Italy, Greece and UK, adopted national measures to avert the crisis, such as offering subsidies to energy providers and imposing price caps, in order to shield citizens from rising electricity costs as their economies recover fully from the COVID-19 pandemic (Ozili and Ozen, 2021). On the other hand, consumers are interesting in ways that help them reduce their energy consumption without compromising their needs. A technological advancement that contributed to this issue is the ability to turn most of the devices that people use daily into *smart* ones (Tom et al., 2019). With the rise of 4G and more recently 5G, these smart devices are able to connect to the internet and be utilized by the user remotely. Nowadays, bulbs can turn off when a person leaves the room, thermostats can adjust to energy needs on the fly, other appliances can notify the user of energy leaks and much more. The idea that led to this is the Internet of Things (IoT), a network of physical objects that use sensors, software and other technologies to connect to each other and exchange data between them over the internet. Grids and Smart Homes, along with significant Information and Communication Technology developments, will leverage the future energy system paradigm, where digitally based marketplaces will allow consumers to easily trade energy and services (Soto et al., 2021).

Contribution

In the current work the goal was to forecast energy demand at the level of individual residence. To this end, we installed smart sensors in over 20 different residences to gather energy and (indoor) weather related readings. We also dealt with the quality of the data coming form the sensors. We evaluated machine learning models for time-series to predict the daily energy consumption over a period of one week. In particular we applied ARIMA models, FB Prophet and LSTM Neural Networks. Furthermore, a dash-

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board was developed for visualizing historical and forecasted data. The dashboard can be accessed by the end customer, or remotely by the electric company.

The rest of the paper is organized as follows. In Section 2 we refer to previous work on energy prediction. Then in Section 3 we refer to the forecasting models and also to the dashboard that was designed. Following, Section 4 refers to data harvesting, and data quality issues. Forecasting results are presented in Section 5. Finally, conclusions are drawn in Section 6.

2 RELATED WORK

There have been many efforts to predict energy demand, but the prediction task differs depending on the time horizon, e.g. long-term, medium-term or short-term; the focus on the prediction, for instance average energy demand over peak energy demand and whether features beyond past samples of energy demand are used. Moreover, pre-processing of the data as well as handling data quality issues is important.

For instance in (Chaturvedi et al., 2022), the authors compared various time-series models to predict total monthly and peak monthly demand in India. In particular SARIMA, LSTM RNN and FB Prophet have been evaluated. FB Prophet along with SARIMA have been the most accurate with LSTM being exhibiting lower performance.

Predicting building energy consumption is another area that has been investigated (Bourdeau et al., 2019), (Amasyali and El-Gohary, 2018). Various models have been considered including Autoregressive Models (AR), Artificial Neural Networks (ANN) and Ensemble methods. Also unsupervised techniques, reinforcement learning (RL) and transfer learning have been tried.

The evaluation results are not directly comparable, as they were applied on different not publicly available data sets. However, there has been a recent international competition on a publicly available data set [1] to predict energy consumption on buildings (Miller et al., 2022). This may be a good starting point for the comparison of different models.

3 METHODOLOGY

In this section, the pipeline of the time-series prediction along with a detailed reference to the applied machine learning models is being presented. (See also Figure 2).

3.1 Pipeline of Time-Series Prediction

We address the problem of forecasting the daily energy consumption of residences over a period of one week. We used models based on econometrics: auto-regressive integrated moving average (ARIMA) and its successors, seasonal ARIMA (SARIMA) and SARIMA with exogenous factors (SARIMAX). We also used the FB Prophet and the Long Short-Term Memory (LSTM) Neural Network. The three models were trained using data from 2019 to 2022, and they were evaluated on data from 2022. The evaluation metrics employed were the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and the R-squared (R^2). Finally, there was developed a dashboard to visualize energy and indoor environmental data.

ARIMA Models

ARIMA models are widely used econometric approaches to uni-variate time-series modeling (Box et al., 2015), (Shumway et al., 2000). It is actually a class of models that *explain* a time-series based on its own past values. In particular, it uses its own lags and the lagged forecast errors, so as to predict future values. All three above-mentioned ARIMA variations (ARIMA, SARIMA and SARIMAX) [2] are considered to be tools for time-series forecasting. The difference between ARIMA and SARIMAX is the seasonality and exogenous factors. ARIMA model is characterized by three parameters: p is the order of the AR term, q is the order of the MA term and d is the number of differencing required to make the time-series stationary. SARIMAX requires an extra set of p, d, and q parameters for the seasonality aspect, and an s parameter that is the periodicity seasonal cycle of the data. The parameters of the ARIMA models are usually determined by the auto-correlation function (ACF) and by the partial auto-correlation function (PACF).

Facebook Prophet

Prophet is an open-source tool developed by Facebook in 2017 for the prediction of time-series values (Taylor and Letham, 2018). It has been used in different business applications and is available both in

[1] https://www.kaggle.com/c/ashrae-energy-prediction

[2] https://github.com/statsmodels/statsmodels/tree/main/statsmodels/tsa

Python and R. [3] It is an additive model featuring a decomposed time-series with three components: trend $g(t)$, seasonality $s(t)$, holidays $h(t)$ (optional term) and an error term (ε_t) that stands for random fluctuations that cannot be explained by the model, and which are assumed to be normally distributed.

LSTM Recurrent Neural Network Model

The LSTM Recurrent Neural Network model was proposed in 1997 and it is widely used in forecasting (Hochreiter and Schmidhuber, 1997), (Greff et al., 2016). LSMTs are complex models, i.e. in general they need much more effort to optimize them. Many parameters, such as the number of layers, epochs, batch size, activation functions, optimizer, have to be properly tuned, in order to get the best possible results. We have used the Keras library [4].

Dashboard

A dashboard named *Home Assistant Administrator's Interface* was designed with Microsoft Power BI. [5] The purpose of the dashboard is to allow users to monitor the sensors installed in residences (see Figure 1). The dashboard consists of a homepage, containing the logo of the telecommunications company along with the report's name, and an interactive ribbon on the left part of the page with buttons that allow the user to navigate through several pages.

There are pages dedicated to the residential energy consumption analysis, that display statistical data (e.g. minimum and maximum energy readings). Also it provides energy readings for specific years, months, weeks, or days including the number of detected sensors' malfunctions. A donut shaped chart, a tree-map, and a column chart are constructed, each one depicting the average energy consumption of the residence based on the years, months, and days respectively. The color palette allows the user to inspect and detect the periods of high energy consumption and draw meaningful insights. Lastly, a *Prediction Analysis* page is available, where the user can view the daily predictions of the energy consumption over a week for each model developed on the project, as well as the actual energy readings. There is an additional card containing the evaluation metrics (MAPE, MSE, RMSE and R^2) of each prediction model and another one for the execution time in seconds. A gauge visual depicts the average of the residuals of each model, along with the minimum and maximum values and another card shows the percentage of days that were predicted over the whole spectrum of days contained in the data set. The column chart is utilized for the comparison of the actual and predicted consumption values per day and uses a line to show their residuals.

All report's pages are interactive and contain arrow and navigation buttons to move to the next page and to a chosen analysis tab, respectively.

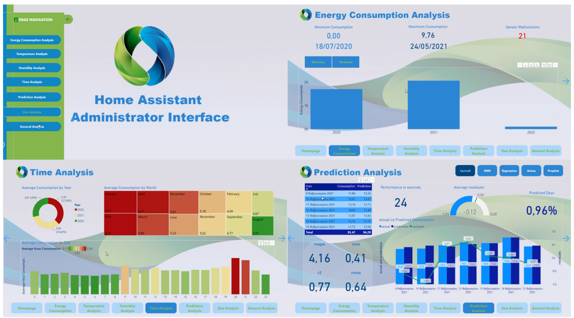

Figure 1: A user dashboard to monitor residential sensors.

4 DATA SET HARVESTING

We retrieved data from the smart sensors installed in two residences, to train models for energy consumption forecasting. A Non-Disclosure Agreement (NDA) was signed between the OTE Academy, [6] a subsidiary of OTE, which is one of the largest telecommunication companies in Greece, and the authors. Since the smart sensors collected personal information of the customers, it was ensured that the whole process would comply with the General Data Protection Regulation (GDPR). [7] The NDA required to handle all data with strict confidentiality, and take all the appropriate measures so the data is stored safely and used only for the purpose of the current work.

Environmental sensors have been installed in the two residences that measure *indoor humidity* and *indoor temperature*. Moreover there are power meters installed at the residences' switchboards which record *power* and *energy* consumption. All the data were harvested and subsequently stored in InfluxDB, [8] a time-series highly optimized database. The data were retrieved from InfluxDB in a JSON format to facilitate post-processing and interoperability with other system components.

The data set was enriched with weather data, and in particular with the *outdoor temperature* and *out-*

[3] https://github.com/facebook/prophet

[4] https://www.tensorflow.org/api_docs/python/tf/keras/layers/LSTM

[5] https://powerbi.microsoft.com/en-au/

[6] https://oteacademy.gr/en/

[7] https://www.gdpreu.org/

[8] https://www.influxdata.com/

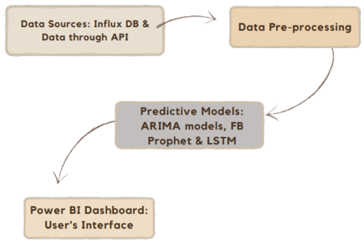

Figure 2: The pipeline of the energy consumption prediction.

door humidity. These data were collected through a free API from the World Weather Online. [9]

4.1 Data Description

As a proof of concept, we used data from two different residences, both of which are situated in Athens, Greece. The installation of the first sensors to the residences started in June 2019, and data were collected from that time and for a period of two years. We have also collected weather related data for the same period. Both the sensor and weather data refer to hourly data points. Some descriptive statistics of the acquired sensor and weather related data sets are depicted in Table 1.

Table 1: Statistics of the data sets (2019–2022).

Residence 1

	cumulative energy $[kWh]$	power $[W]$	temperature $[°C]$	humidity $[\%]$
mean	2296.50	19881.96	21.14	62.44
std	1554.35	60317.96	4.13	8.75
min	5.39	-40980.86	13.03	32.07
max	27083.62	3623000	31.83	85.73
missing values	5.53%	5.53%	3.85%	3.85%
#samples	*24,239*	*24,239*	*19,904*	*19,904*

Residence 2

	cumulative energy $[kWh]$	power $[W]$	temperature $[°C]$	humidity $[\%]$
mean	7350.65	2388.58	20.85	67.49
std	2043.66	7790.89	4.06	12.18
min	3498.92	0	13.25	30.33
max	13861.59	140739.83	30.90	99.52
missing values	3.21%	3.58%	4.07%	4.07%
#samples	*23,852*	*23,760*	*14,003*	*14,003*

4.2 Data Quality

Poor-quality data is often pegged as the source of operational snafus, inaccurate analytics, and ill-conceived business strategies (Batini et al., 2016). Besides, the main challenge of this study was the data pre-processing phase, since data in the real world is often dirty and corrupted with inconsistencies, noise, incomplete information, and missing values, and therefore data quality should be recognized and addressed.

[9]https://www.worldweatheronline.com/

The first step was the exploration of the raw data to detect any sensor malfunction before performing pre-processing. Both energy and weather data collected by the power meters and the environmental sensors were examined in terms of data quality, as any detected inconsistencies directly affect the performance of the predictive models.

Energy Related Sensor Malfunctions

Erroneous readings from the power meters were related to many causes. First, internet connection disruptions, and power failures resulted in missing values. Second, hardware problems caused lags. This resulted in energy values that were constant for extended periods of time or even resulted in energy spikes, which is unusual (see Figure 3).

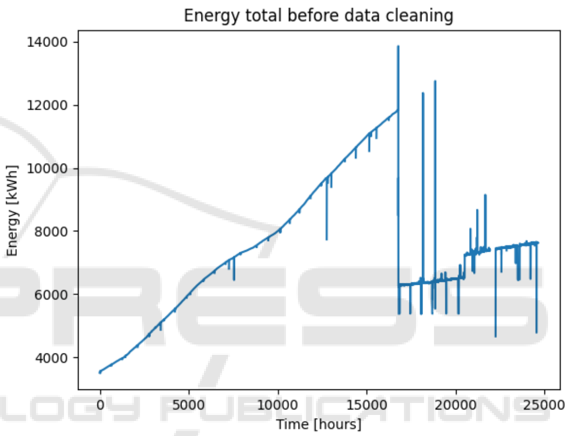

Figure 3: Cumulative energy through time: At about 16,000 hours the curve drops from about 12,000kWh to about 6,000kWh. A clear case of sensor malfunction.

Environment Related Sensor Malfunctions

A rough way to check for sensor lags is by visually inspecting the time-series. For instance, Figures 4 and 5 depict temperature and humidity over time. Missing values occurred at about 12,000 hours (about 1.5 years from the beginning of the time series). Also, some very prominent spikes are indicative of some malfunction.

4.3 Feature Extraction

The extraction of temporal features was proven critical in analyzing the energy consumption of the residences. The exact hour, day, month and year as well as the time intervals that correspond to working hours, or to busy hours were essential pieces of information. We used the Python holidays library [10] to iden-

[10]https://python-holidays.readthedocs.io/en/latest/#

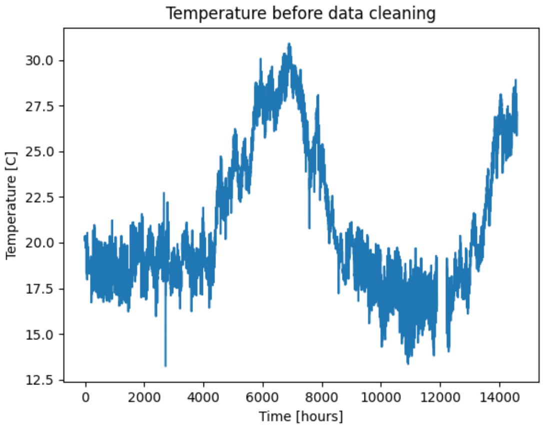

Figure 4: Indoor temperature, missing values around 12,000h.

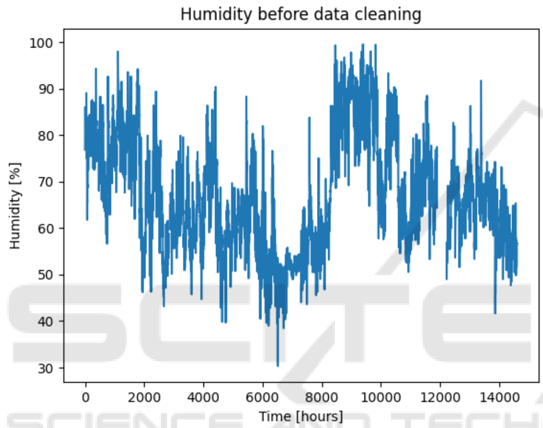

Figure 5: Indoor humidity, missing values around 12,000h.

tify Greek holidays, a factor that could likely affect the energy consumption, as on public holidays people behave differently. Moreover, features related to the sunrise, sunset time, and daylight duration were extracted from information included in the weather data.

Finally, since the sensors reported cumulative energy, we had to subtract two neighboring values to obtain the *energy consumption per hour*. The training data set comprised hourly measurements. The forecasting was performed on a daily basis for up to 7 days (see Table 2 for an overview of the data features).

4.4 Data Cleaning

Sensor malfunctions affected to a great extend the data quality. In particular we detected and addressed the following types of data quality issues: *missing values, outliers* and other *suspicious data*.

First, we applied a z-score value of 4 to remove *cumulative energy, indoor temperature* and *indoor humidity* outliers. Then, we replaced the missing environmental values with their adjacent values by utilizing the forward fill function of Pandas in Python; this propagates the last valid observation forward [11].

Following that, we dealt with the *suspicious* energy values that are due to hardware problems, including internet connection disruptions and power failures. This caused missing values. Sensor malfunctions caused lags that occurred for extended periods of time. This was observed as constant energy values or as energy spikes.

As far as the malfunctions due to internet connection issues were concerned, we replaced the *missing energy values* by the mean and smoothing the line between those two points, since we had two correct points of reference. That was possible due to the fact that after the internet connection was restored, the sensor's measurements would revert to the correct energy values.

Addressing the *energy spikes* and the *constant energy* values was more challenging. First, we performed time-series data visualization with Grafana. [12] We observed that the sensors were lagging for extended time periods, as they were returning the same energy value for the many consecutive time steps.

- For the *energy per hour* feature (see also Section 4.3), the z-score outlier detection method was applied again to remove any *abnormally high energy values*. These values were then replaced with their *adjacent energy* values by using the forward fill function of Pandas. Such values were observed in a few occasions, something that could be the result of a sensor's malfunction or an extreme but still actual event.
- The detection of the *constant energy* values was based on domain experts' advice that the minimum energy consumed at each data point should be more that 0.06kWh. Thus in the case that we detected a series of 3 or more consecutive data points in the time-series where the energy consumption was below that threshold, the values were replaced with the *mean* value of their adjacent ones. Constant energy values lasting for a whole month values were observed in residence 2. It was an extreme case of corrupt values in terms of duration.

5 FORECASTING RESULTS

In this section we report the forecasting experiments with ARIMA, SARIMA, SARIMAX, FB Prophet and

[11] https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.ffill.html

[12] https://grafana.com/

Table 2: Extracted features of the time-series data.

Feature Name	Format
Time-based features	
Year	timestamp (form: 2019)
Month	timestamp (form: Jan 1 - Dec 12)
Date	timestamp (form: 2019-06-27)
Day	timestamp (form: 27)
Day of week	timestamp (form: Mon 0 - Sun 6)
Time	timestamp (form: 09:00:00)
Hour	timestamp (form: 9)
Weekday	1 if day of week < 5, else 0
Working Hours	1 if hour in range [9:00, 18:00] & day of week <= 5, else 0
Busy hours	1 if hour in range [7:00, 9:00] or [19:00, 00:30] in weekdays or hour in range [9:00, 15:00] in weekends
Holiday	NoHoliday, MondayoftheHolySpirit, EasterMonday, IndependenceDay, DayafterChristmas, Labourday, OchiDay, Epiphany, CleanMonday, AssumptionofMary, NewYearsDay, Christmas
Weather-based features	
Sunrise	conversion to strptime() (form: 1561601100.0)
Sunset	conversion to strptime() (form: 1561654320.0)
Is day light	1 if *sunrise* ≤ *time* ≤ *sunset*, else 0
Sensor-based features	
Energy per hour	energy value (form 0.0)

LSTM models, along with their evaluation.

In ARIMA, SARIMA and FB Prophet, the energy, date and year features of the data were selected. In SARIMAX the environmental parameters indoor temperature and humidity were included as the exogenous variables. Finally, in the LSTM the energy, indoor and outdoor environmental parameters along with the features listed in Table 2 were selected.

ARIMA Results

First we considered ARIMA models, to provide a baseline performance benchmark with which to compare the rest of the models. Overall it has a poor performance. This was due to the fact that although ARIMA can handle data with an underlying trend, it fails to support time-series with a seasonal component. The model's performance is depicted in Figures 6 and 7 for residences 1 and 2 respectively.

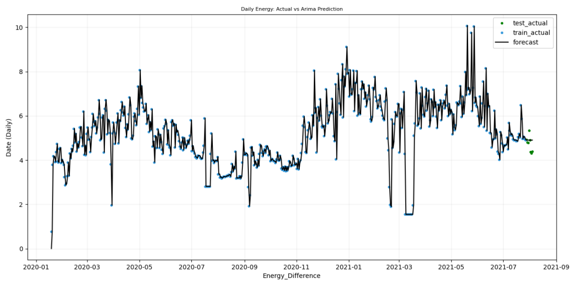

Figure 6: ARIMA Forecast for Residence 1.

In an attempt to improve the prediction, ARIMA's successors SARIMA and SARIMAX were applied. A grid search discovered the best parameters for the model with the augmented Dickey-Fuller (ADF) and Akaike Information Criterion (AIC) metrics.

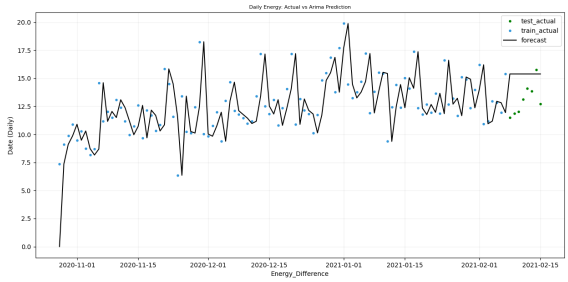

Figure 7: ARIMA Forecast for Residence 2.

The best results were for $(p,d,q) = (0,1,0)$ and for $(P,D,Q,M) = (1,1,1,7)$, where the (p,d,q) and (P,D,Q,M) terms refer to the order of the time-series and the order of the seasonal component respectively.

The experiments have shown that SARIMA with only the energy feature, resulted in slightly better predictions compared to SARIMAX, that included the indoor temperature and humidity values (See Figures 8 and 9 for the results).

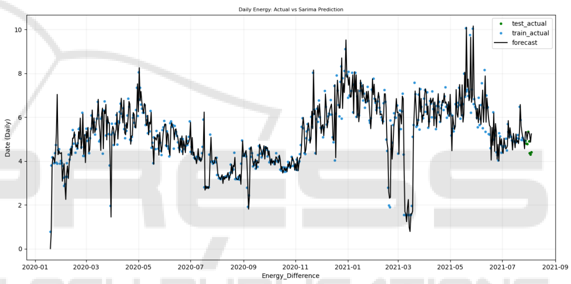

Figure 8: SARIMA Forecast Line Plot for Residence 1.

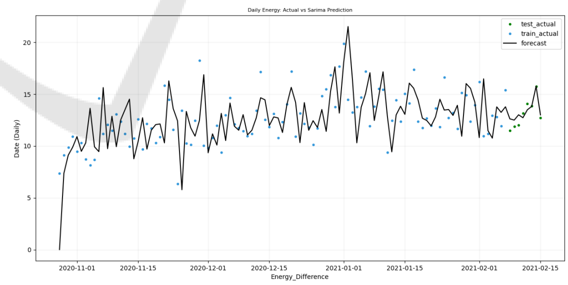

Figure 9: SARIMA Forecast Line Plot for Residence 2.

Facebook Prophet Results

In FB Prophet the trend changepoints prior scale (τ) and seasonality prior scale (σ) hyper-parameters can be tuned so that the model fits data optimally. After experimentation, the daily, weekly, and yearly seasonality parameters of the model were set to true, whereas the period indicating the number of the prior periods that are important for the prediction was set to 1. The last parameter that we considered was the Fourier order, which is responsible for estimating the seasonality and whose value was set to 8.

After selecting the best values of the parameters, we employed them to evaluate the FB Prophet model in the test phase. The results for the two residences are presented in Figures 10 and 11 respectively.

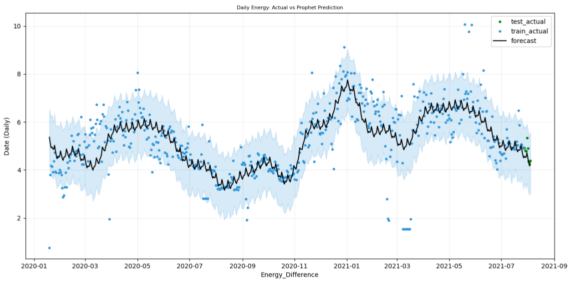

Figure 10: FB Prophet forecasting for residence 1.

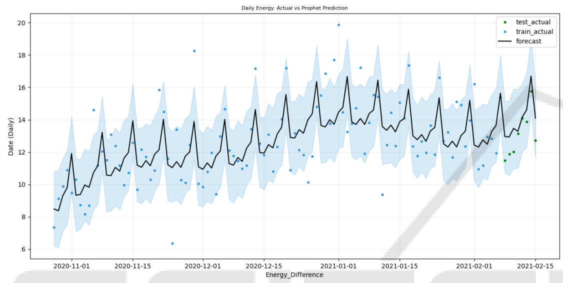

Figure 11: FB Prophet forecast for residence 2.

The FB Prophet offers additional features as external sources, such as custom holidays, vacation days, and even a custom seasonality that could be based on the user's behavior. However, since the predictions were pretty accurate, the exploration of these features was left for future work.

LSTM Recurrent Neural Network Results

The architecture of the LSTM in Keras [13] consists of an LSTM layer, dense and dropout layers for prevention against over-fitting. The Adam optimizer was used, and the optimization was based on mean squared error (MSE). Finally, the model was trained for 10 epochs with a batch size of 64. The forecasting lines of the LSTM model for both residences can be observed in Figures 12 and 13.

Comparison of Models

We rated the performance of the models on the time-series data based on the MSE, MAPE, RMSE (lower values are better) and R^2 (higher values are better) metrics. The results for both the training and testing phases, along with the models' execution time are

[13] https://keras.io/

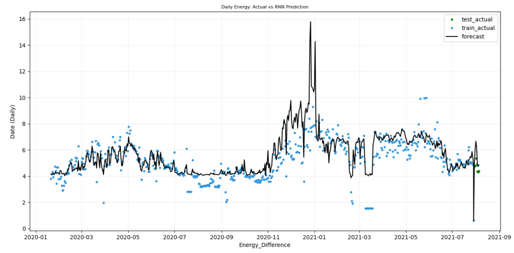

Figure 12: LSTM Forecast Line Plot for Residence 1.

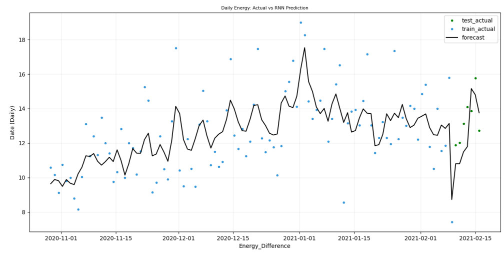

Figure 13: LSTM Forecast Line Plot for Residence 2.

presented for both of the residences in Tables 3 and 4.

Table 3: Evaluation metrics for residence 1.

Training set residence 1					
Models	MSE	MAPE	RMSE	R^2	Execution time [sec]
ARIMA	0.76	0.87	11.26	0.62	47
SARIMA	0.78	0.88	12.05	0.61	47
Prophet	0.93	0.96	16.96	0.53	48
LSTM	1.32	1.15	16.48	0.35	59
Testing set residence 1					
Models	MSE	MAPE	RMSE	R^2	Execution time [sec]
ARIMA	0.14	0.37	6.37	-0.27	47
SARIMA	0.29	0.55	10.49	-1.72	47
Prophet	**0.11**	**0.33**	**5.75**	**0.02**	48
LSTM	0.78	0.88	15.98	-5.55	59

6 CONCLUSIONS

In the current work we tried to forecast the energy consumption in two residences. We used data collected from sensors in the residences (energy consumption and environmental data) as well as weather data (outdoor data). We dealt with data quality issues stemming from the operation of the sensors and the internet connection.

Different models were tested for forecasting the energy consumption. The best models were as expected the SARIMA and FB Prophet that had a good accuracy. As far as the LSTM's performance is concerned, there was evidence that further optimization of its parameters would improve its results.

Overall the models that used only the energy consumption feature to make predictions had a better performance. This was probably caused because the

Table 4: Evaluation metrics for residence 2.

Models	MSE	MAPE	RMSE	R^2	Execution time [sec]
Training set residence 2					
ARIMA	8.20	2.86	18.32	-0.37	24
SARIMA	8.23	2.87	18.81	-0.37	24
Prophet	3.18	1.78	11.23	0.47	24
LSTM	2.67	1.63	11.11	0.53	29
Testing set residence 2					
Models	MSE	MAPE	RMSE	R^2	Execution time [sec]
ARIMA	6.90	2.63	19.02	-2.92	24
SARIMA	**0.41**	**0.64**	**4.16**	**0.77**	24
Prophet	1.09	1.05	7.19	0.38	24
LSTM	1.96	1.40	9.95	-0.26	29

available data set was not large enough. Also the data were collected during the COVID-19 pandemic, when the subsequent lockdown periods caused an unusual behavior on the part of the consumers. The data were collected over the past three years, but each year was different. In 2019 the residents' behavior was normal, since there was no lockdown, but in 2020 all changed since people had to stay at home and thus the energy consumption increased (Abu-Rayash and Dincer, 2020). Abnormalities like these heavily affect the data especially in the seasonality aspect, that is crucial for time-series data as the ones in hand. This might be the reason of models performing worse when no external data are utilized, since the target variable that is used is compromised. Moreover, all the models, except FB Prophet performed worse with large sizes of training data. The FB Prophet had better performance with a larger size of training data.

Concluding, the forecasting models are part of a software service that is accessible via a dashboard. The service can be used by the customer to monitor historical energy consumption, obtain predictions and thus to draw conclusions providing a better understanding of the residence's energy consumption, and to possibly take actions in economizing. The service can also be used by the electric company to acquire sensor data from all residences. The company could possibly "intervene" in the residence by switching off unused smart plugs should they have the customer's consent; or even to suggest ways to reduce the residential energy consumption by replacing old and inefficient domestic appliances, i.e., oven, fridge, washing machine.

The current work can be expanded in several directions. First, we can try to predict energy consumption based on all 20 residences instead of only 2. Second, as data continue to be gathered we could enhance the training data sets. Finally, we could try different forecasting models such as the transformer networks.

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