Partial Hierarchy Appliance Modelling In Household Energy Consumption

Utilizing ARMA based methods to improve the prediction of household energy consumption

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Abstract

The ever-evolving power grid is becoming smarter and smarter. Modern houses come with smart meters and energy conscious consumers will buy additional smart meters to place in their home to help monitor their energy consumption. This new smart technology also opens the door to more accurate power consumption forecasting. In this study we look at utilizing a partial hierarchy, in which one of the appliances in a household is modelled separately from the rest of the house, to help improve household energy consumption forecasting accuracy. This is done in conjunction with Auto Regressive Moving Average (ARMA) based models. Three variants of ARMA based models will be looked at: Auto Regressive Integrated Moving Average (ARIMA), Seasonal Auto Regressive Integrated Moving Average (SARIMA), and Auto Regressive Integrated Moving Average with Exogenous variables (ARIMAX). These methods will then be compared to more baseline approaches such as a persistence method and a seasonal moving average. Our analysis has led us to conclude that the partial hierarchy model offers little to no benefit when applied in the field of household energy consumption forecasting when built upon ARMA based models. ARMA based models in general appeared to be poor performers when it came to household energy consumption forecasting.

1 Introduction

The modern-day energy grid is ever evolving in order to meet demands. While the energy grid from fifty years ago was a relatively simple system, our ever-growing dependency on electricity has required the grid to grow and evolve. While the grid has been steadily growing, the way we use the grid has also changed. Individual people have become large power consumers outside of work hours and many are installing solar panels to help power the grid. This creates a wave of supply and demand in the power grid. The peaks introduced by this wave can be very costly. Spees and Lave [1] estimate that if only 5% of the electric load in a day can be shifted, an overall peak load of 15.8% can be saved resulting in a 10.5% decrease in energy price for the end consumer. The main reason behind this cost saving is that fast response energy generators are also the most expensive to run. And that while more efficient generators could be used, they often are not economically viable for the short load time [2].

While the grid has been steadily growing it is only recently that smart meters have become ubiquitous in our homes [3]. By analysing a consumers behaviour and modelling their energy consumption, energy providers can play into the supply demand wave and attempt to flatten the curve. To this extent this research will investigate each device their energy consumption and attempt to create a prediction for the energy consumption of the home itself. This would allow energy providers to save costs as increasing energy grid efficiency by only a small amount could lead to giant cost saving [1].

Seasonal Auto Regressive Integrated Moving Average with Exogenous variables, SARIMAX, models are a type of time series forecasting model which are already frequently used in the field of energy consumption prediction [4–6]. Many variations of this model exist but the baseline is the Auto Regressive Moving Average, ARMA, model. This technique can help understand and even predict future values of a signal. The ARMA model can be adapted in many ways but for this paper three components are of interest. The first component is integration. An ARMA model requires its input data to be stationary. If this is not the case the difference between two lags, consecutive data points, can also be utilized as input, this is known as ARIMA. Secondly the model can also be extended to account for periodicity in the data. In this case apart from its regular AR and MA lags it will also keep track of seasonal AR and MA values, combining this with ARIMA is known as SARIMA. Finally, an exogenous component which allows the model to take into account other trends that might be correlated, such as outside temperature, can be added for the final generalization known as SARIMAX. A more in depth explanation can be found in section 3.

Research Question

For this research project the following question will be answered: ”Can the forecast accuracy for a single household be improved by using a partial hierarchical structure when using an ARMA based method?”.

Together with the main question the following subquestions will also be pursued:

- How do simple persistence methods compare to ARMA based methods?
- What devices, when modelled separately in the hierarchy, lead to the largest improvement of accuracy?

The rest of the paper is organized as follows. Initially related work will be discussed in section 2. In section 3 current ARMA based techniques are discussed. Section 4 discusses the data that will be utilized as well as how the methods will be compared. Section 5 goes over the experimental setup and testing environment. This is then followed by the results in section 6. Section 7 then goes into the ethical issues of the problem that this paper is focused on. Afterwards the results are interpreted and conclusions drawn in section 8. Finally section 9 summarizes the paper, recommends future avenues of research, and concludes the paper.

2 Related work

ARMA based models are not new in the field of energy consumption forecasting and have been utilized with success. Ediger and Akar [7] have used ARIMA to help forecast primary energy demand in Turkey. Atique *et al.* [8] Utilized ARIMA to help predict daily solar generation, while also stating that: ”the beauty of the ARIMA model lies in its simplicity” [8]. Nepal *et al.* utilized a combination of K-means clustering together with ARIMA to gain an increase in accuracy when forecasting the energy consumption of buildings. This shows that ARMA based models are a relatively simple technique, making them easy to apply, whilst also being adaptive as they can benefit from combining with different techniques.

Yet, ARIMA might not be the most optimal technique to predict aggregated power consumption, Al-Mussaylh *et al.* [9] found that MARS and SVR techniques can greatly outperform ARIMA. Veit *et al.* [4] compared ARIMA to methods such as BATS or NNET on the subject of household electricity demand forecasting and concluded that: "state-of-the-art forecasting methods rarely beat corresponding persistence forecasts". While ARIMA can be a great tool for forecasting a direct signal, there is also a strong seasonal aspect at play when dealing with energy consumption which could help improve accuracy when taken into account. Some studies attempt to use a seasonal component to ARIMA [10, 11] but their main focus is on some form of quarterly or monthly consumption.

Javed *et al.* [12] shows that predicting household energy consumption is much more difficult than forecasting a larger grid, with standard deviation of rate of change being two orders of magnitude larger for a single household. Apart from that, bottom up forecasts are generally more expensive than top down. Zhen *et al.* [13] solved this problem by using a recontextualized Kalman filter to keep computational costs low. Alternatively the bottom up model could also be constructed as a series of random variables for each appliance, indicating how often and intense the device is used [14]. Such an approach would take a while to train but once the correct probability density functions are acquired could provide real time feedback.

Most research focuses on either simulating all appliances or just the aggregate of those appliances. But whether either of these techniques lead to an overall improvement is up for debate as it can be heavily dependent on the data set used [4]. This leaves the door open for a model that will remove some devices from the aggregate and model them separately in order to improve accuracy.

3 ARMA techniques

3.1 Predicting via ARMA

ARMA models consist of two main components: auto regression, AR(p), and a moving-average model, MA(q). The AR component is also known as an autoregressive process of order p [15]. This model is defined as shown in formula 1 [15].

$$X_t = \Sigma_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \tag{1}$$

In this model X_t represents the value to be predicted at time t and it is calculated by summing up the last p preceding values X_{t-i}, also known as lags. Each of these lags is multiplied by a parameter φ that is calculated during the fitting process of the method. Finally a sample of white noise ε_t is drawn from a normal distribution and added to the final sum. The resulting model can also be viewed as a moving weighted average model to which an amount of noise is supplied.

The MA component is known as a moving-average process of order q. The moving-average process is a series of white noise terms that are added up according to the following definition given in formula 2 [15].

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{2}$$

In this model X_t represents the value to be predicted at time t and it is calculated by summing up the last q white noise terms multiplied by a parameter θ, which is also calculated during the fitting procedure. To this is then added the expected value of the signal μ and another white noise term ε_t. The result is some signal that moves around the mean value of the input signal. Both of these models are already useful in helping model and understanding a signal and can be combined to create an ARMA(p,q) model. This new ARMA model can be applied more generally relying on the strengths of both models in order to reach parsimony. In this combination the μ term in the MA model, formula 2, gets replaced by the AR model and the white noise term gets dropped from the MA model. This results in the following definition [15]:

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{3}$$

3.2 Predicting via SARIMAX

A SARIMAX model is the combination of three techniques added to an ARMA model. The first extension is integration. The second extension is seasonality. And the third extension is exogenous data. The integration extension introduces a new hyper parameter d with a domain of natural numbers. This extension is known as ARIMA. If the original signal is not stationary, as is required for ARMA to function, ARIMA is used to difference the data d times before applying an ARMA model. The procedure of differencing for non zero orders of d can be described by the recursive formula 4.

$$\begin{aligned} X_t(0) &= X_t \\ X_t(d) &= X_t(d-1) - X_{t-1}(d-1) \end{aligned} \tag{4}$$

In which X_t returns the data entry from point t and d resembles the order of differencing. While another techniques such as fractional integration exists it is not discussed in this paper.

The second extension is Seasonality, it introduces a new set of hyper parameters $P, D, Q,$ & m all with a domain of natural numbers. This extension is known as SARIMA. This new version also known as Seasonal-ARIMA takes into account a signal that has a certain periodicity of size m in it. e.g. when dealing with quarterly data $m = 4$. The parameters of P, D, Q are similar to the parameters p, d, q but instead of dealing with directly preceding lags they deal with the respective seasonal lags, lags offset by the frequency m. A Seasonal-ARIMA model can be described as two ARMA models added together, one dealing with preceding lags and one dealing with preceding seasonal lags. This is reflected in formula 5 [15] where the new seasonal component is highlighted in blue.

$$\begin{aligned} X_t = \varepsilon_t &+ \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \\ &+ \sum_{i=1}^{P} \Phi_i X_{t-im} + \sum_{i=1}^{Q} \Theta_i \varepsilon_{t-im} \end{aligned} \tag{5}$$

Finally the model is extended with exogenous information. This introduces no new hyper-parameters but instead one or multiple parameters to the model. This extension is known as SARIMAX. The new parameter added is a signal the same size as the input signal carrying additional information, such as temperature or house occupancy. This allows the model to respond faster to direct changes. One of the main downsides of this extensions is that for future prediction the future signal of exogenous information will need to be provided before a prediction can be made. The exogenous variables are described by formula 6 and are represented by m_t. It can be viewed as a sum of constants η_i multiplied by the exogenous variable y at time $t-i$ together with some constant c. The final SARIMAX formula can the be constructed by adding this m_t to the SARIMA model as shown in formula 7 [16] and highlighted in olive.

$$m_t = c + \sum_{i=0}^{b} \eta_i y_{t-i} \tag{6}$$

$$\begin{aligned} X_t = \varepsilon_t + c &+ \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \\ &+ \sum_{i=1}^{P} \Phi_i X_{t-im} + \sum_{i=1}^{Q} \Theta_i \varepsilon_{t-im} \\ &+ \sum_{i=0}^{b} \eta_i Y_{t-i} \end{aligned} \tag{7}$$

A SARIMAX model therefore has seven main hyper-parameters, p, d, q, P, D, Q & m, out of which m is often predefined by the periodicity. These parameters will need to be defined before the model is fitted on the testing data. In order to determine these parameters the auto_arima functionality from pmdarima [17] was used. This function takes in bounds for the parameters and attempts to find the most optimal combination for the given training data via either a grid search or a step-wise approach.

3.3 Featurizers

Featurizers can be employed to make data more machine learning friendly. They are often employed in areas where the RAW data is too complicated to be directly modelled. In those cases a featurizer is employed to create alternative data that represents the original raw data in a more structured way. Such as spectograms in the field of speech recognition or edge images in the field of computer vision.

These featurizers can also be extended to the field of household energy consumption prediction. Hyndman, R. [18][1] suggests that instead of utilizing Seasonal-ARIMA when dealing with large $m > 12$, as those methods are not designed for such long periods, one can also use a featurizer beforehand. This featurizer would extract the seasonal elements from the original signal and feed them back into an ARIMAX model with the featurized data as exogenous data. In this specific instance a Fourier featurizer is used. It disaggregates the original signal into a series of signals that can each be described by a sine and a cosine. These individual signals are then fed back into an ARIMAX model together with the original data. This is proposed as an alternative to Seasonal-ARIMA as it avoids the large memory consumption from Seasonal-ARIMA. The benefits of this featurized approach are a decreased fit time, multiple seasonal frequencies support, and still utilizing ARMA to deal with short-term dynamics [18].

A Fourier series was originally intended to work on continuous signals. There also exists the Discrete Fourier Transform, DFT, which can be applied on discrete data points as follows. First a series of complex constants X_k where k goes from 0 up to $N-1$ need to be calculated as shown in formula 8 [19].

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N} \tag{8}$$

In this case N represents the total number of datapoints, x_n represents the datapoint at position n. k does not need to go up all the way to $N-1$ but doing so will lead to a higher accuracy. k represents the number of periods per N datapoints, high values for k mean more fine tuned systems are introduced, while low values often detect larger patterns. With the complex constants of X_k calculated we can reverse this transformation to calculate x_n via formula 9 [19].

$$x_n = \frac{1}{N} \sum_{k=0}^{N-1} X_k \cdot e^{i2\pi kn/N} \tag{9}$$

As $e^{i2\pi n}$ is periodic we can use this inversion to also calculate values outside of the range $[0, N]$ as long as $n \in Z$. However, the featurizer will construct each of these waves up to $k = m/2$ separately and feed them into the ARIMAX model. This allows the ARIMAX model to decide which components are useful when taking into account the seasonality.

4 Methodology

4.1 Data usage and validation

The data consists of fifteen minute measurements of each device in a household over a series of households collected by Pecan Street [20]. They are an energy monitoring company aiming to accelerate climate and conservation solutions. In particular we will be using their fifteen minute interval New York data set. This data set was chosen as it's one of lower granularity and has a higher data integrity, the main reason for those interests is a lower runtime. This data is first grouped by household and then converted to hourly data by taking the mean of every four data points. The data is then split into two sections, training and testing. The training data will solely be used to find the hyper parameters for each model and will be input as one large chunk. The test data will be split up into chunks via a sliding window containing a number of $n > 1$ whole days of which the first $n-1$ days will be used as input and the last day the actual signal to compare to the prediction.

[1] While the source leads to a blog post Rob J Hyndman is well known in the field of time series forecasting with multiple books and articles published.

A day starts at 00:00 and ends at 23:45 resulting in 24 data points in a day

The accuracy of the predictions will then be established. This will be done via series of metrics:

- RMSE, Root Mean Squared Error.
- MAPE, Mean Absolute Percentage Error.
- MAE, Mean Absolute error.
- MRE, Mean Relative error.

For all metrics it holds that a lower score is preferred. These metrics were chosen as they have shown up most predominately in other work [4,9,21]. Thus utilizing them here would lead for easier comparisons with the rest of the field.

As no household is the same, comparing between them is difficult. Each household has a different set of appliances and they are all used in different ways. This makes it impossible to calculate the effects of a system of which only a part is removed to be modelled separately, a partial hierarchy, and to then compare it to all houses in the data set. e.g. It could be that houses that have an electric car are easier to predict in general, the electric car is a large yet regular consumer. However, this would mean that when applying the partial hierarchy on such a house, even if the technique has no effect, the average score over this subset of households would be lower than the average score over all households. Initially it would seem like an improvement has taken place, the score of the electric car partial hierarchy is lower than the total grid score, the score of the models predicting just the total energy consumption. Yet this might not be the case. To remove this bias each device category will need to weighed against its own total grid score. Meaning, the electric car partial hierarchy will be compared only to the total grid scores of houses that have electric cars themselves.

4.2 Baseline algorithms

In order to compare the predictions to a series of trivial solutions two solutions are presented. The first trivial solution is known as the persistence method. This takes in the last value of the input signal and repeats it for as many forecasts as requested, more specifically in this case it will return the last day of the input sample as the prediction. The second trivial solution is the moving average. This solution will take in the input signal and calculate the mean of the seasonal lags and return that as its output signal.

5 Experimental setup

For each iteration, consisting of a house and one of its appliances, three models were made. First a model was required to predict the total energy consumption of the household, this will be called the total model. Secondly a of model for each device was created, known as the device model. Lastly another model was trained on the partial energy consumption of a household, a model responsible for predicting the total power consumption minus the consumption of the device in the iteration, known as the partial model. The predictions from the device and partial models would be summed up to create a partial hierarchy for each device respectively to result in a singular model, the test model.

All three models would be asked to create predictions based on the test data. The predictions of the device and partial model would be summed up to one signal. Then the remaining two signals would be compared to the ground truth.

5.1 Evaluation

In this experiment five methods were compared:

- The persistence method.
- The moving average.
- ARIMA.
- SARIMA with $m = 24$.
- ARIMAX utilizing a Fourier featurizer.

From the data set the first month was utilized to perform hyper parameter tuning. If a model did not require hyper parameter tuning the month was discarded. The remaining five months were then fed to the models via a sliding window. The models were reset after each iteration of the sliding window to avoid knowledge bleed over. This sliding window incorporated eight days. The first seven of which would be used as input data for each model to predict the eighth day which acted as the reference solution. After this the predictions were measured by taking the previously mentioned metrics. The total grid scores for each device was also calculated by averaging out only the total grid scores from households that had the device present. For a device to be retained into the final result at least three houses needed to have the device registered.

6 Results

The SARIMA method timed out when running on the larger data set, more on this can be read in section 8. Therefore only the results for the ARIMA and the ARIMAX techniques will be shown when talking about the ARMA methods.

Performing this experiment we obtain the following results. When considering only the total signal we get the following average scores for each method and their critic.

critic	ARIMA	Moving Average	Persistence	ARIMAX
MAE	0.33785	0.30631	0.33915	0.31913
MAPE	228.40	178.00	178.03	197.94
MRE	0.03491	0.00262	0.00199	0.00679
RMSE	0.55112	0.52721	0.66903	0.52979

Table 1: Scores per metric for each method considering only the total output of a household.

Consolidating the data, the following four tables will show all devices that saw an improvement in accuracy over all of the total models. To further explain, if the device is in one of these tables it means that using the technique under test and creating the device and partial model beats all of the techniques used on the total signal. The test column tells us which technique (AX for ARIMAX, AR for ARIMA, PE for persistence, and MA for moving average) lead to the overall best result when using a partial Hierarchy. The total column describes which technique was most effective on the total signal. The accuracy columns describe the metric score for the test and total techniques respectively. The relative column shows how much the accuracy score has improved relative to the score of the total model. Defined as $(|total\_acc| - |test\_acc|)/|total\_acc|$.

Out of the 44 devices present in the data set only 22 were present in three or more households. This means that with four metrics there are a total of 88 device metric combinations. Suffixes indicating which specific freezer have been removed for clarity. In this specific case all devices could be suffixed with 1 to compare with the original data set. The names of each device were created by Pecan street and the descriptions come included when downloading one of their data sets.

device	test	total	test acc	total acc	relative
livingroom	AX	AX	111.34	118.21	5.80%
freezer	AX	AX	86.056	89.588	3.94%
air	AX	AX	90.280	93.578	3.52%
refrigerator	AX	AX	104.29	107.55	3.02%
waterheater	AX	AX	126.54	128.89	1.82%
furnace	AX	PE	92.486	93.848	1.45%
lights plugs	AX	AX	91.515	91.896	0.41%

Table 2: All devices with a positive increase when looking at the MAPE metric. 7 of 22 devices saw an increase.

device	test	total	test acc	total acc	relative
bedroom	AX	AR	0.00041	-0.01500	97.2%
wellpump	AX	AX	0.00014	0.00091	83.7%
circpump	AX	AX	0.00057	0.00212	72.7%
garage	AR	AX	-0.00215	-0.00481	55.2%
refrigerator	AX	PE	0.00578	0.00623	7.1%
garage	AX	AX	-0.00457	-0.00481	4.8%
car	AX	MA	0.01722	-0.01793	3.9%

Table 3: All devices with a positive increase when looking at the MRE metric. 7 of 22 devices saw an increase.

device	test	total	test acc	total acc	relative
air	AX	MA	0.33428	0.33870	1.30%
bedroom	AR	AR	0.34960	0.35258	0.84%
pump	AR	AR	0.36082	0.36297	0.59%

Table 4: All devices with a positive increase when looking at the MAE metric. 3 of 22 devices saw an increase.

device	test	total	test acc	total acc	relative
drye	AX	AX	0.56620	0.57476	1.48%
waterheater	AX	AX	0.64642	0.65479	1.27%
air	AX	AX	0.54321	0.54813	0.89%
range	AX	AX	0.58056	0.58286	0.39%
furnace	AX	MA	0.51153	0.51323	0.33%
clotheswasher	AX	AX	0.52114	0.52176	0.11%
bedroom	AR	AR	0.64959	0.65011	0.08%

Table 5: All devices with a positive increase when looking at the RMSE metric. 7 of 22 devices saw an increase.

This in total amounts to 24 out of those 88 combinations being won by an ARMA based method that is utilizing the partial hierarchy. Zooming out, out of all situations in 54 out of 88 combinations does a baseline method win, both from an ARMA based partial hierarchy as well as a total grid signal ARMA based model. 38 of which are won by the moving average and 16 are won by the persistence method.

When viewing just the effects of the partial hierarchy there are 178 categories, 88 ARIMA device-critic combinations and 88 ARIMAX combinations. Out of these 178 categories 100 show an increase in accuracy when the partial hierarchy model is introduced. An abbreviated version of this table, set to include only relative scores $\geq 5\%$, and a table of the full results can be found in appendix A and B respectively.

7 Responsible Research

The nature of such a project as this is quite intrusive. The paper's aim is to properly predict a households power consumption and therefore by extend the behaviour of the people within the household. An argument could be made that one would still require smart meters placed throughout their home in order for this data to become available. However, with energy dis-aggregation techniques becoming more available and accurate the risks should not be discarded. These two techniques, consumption prediction and energy dis-aggregation, could be trained in tandem with each other. Allowing them to eventually function without any smart meters on the net for a considerable time.

And while these models could be run locally by the household in most cases they will be run by a third party meaning personal data will be transferred and analyzed. This project therefore lies in a grey area, as energy is just another product we consume it can be viewed from the same ethical standpoint as shopping cart analysis of large supermarket chains. It is not inherently negative for the user. These processes attempt to tailor an experience that best suits the user, often with deals that appeal beneficial to them. The question that remains is "are those deals really beneficial to them and society as a whole?". And more specifically when dealing with energy consumption. If this model allows for more personal services to what extend do those personal services lead to an overall higher consumption that you originally did not need?

In conclusion, while this technique is interesting and important privacy watchdogs should be aware of the risks and inform both consumers and authorities that this data can also be used to model people's personalities. And although these techniques do pose a risk to a users privacy. If these models are ran locally within a users network there is no risk of personal information leaking out to third parties while still being able to provide both ecological and economical benefits.

8 Discussion

8.1 result summary

In the results we can see that the moving average method scores best with the MAE, MAPE, and RMSE critics. The MRE critic is won by the persistence method. In 24 out of 88 categories did using a partial hierarchy improve the overall accuracy. Most of those increases only occur when an ARMA based method was already the most effective as this relation accounts for 18 out of 24 improvements. In 54 out of the 88 categories did a baseline method beat out the ARMA based models, both total and partially hierarchic. In the remaining 10 scenarios an ARMA based method was most effective yet transforming it into a partial hierarchy-based method deemed ineffective. When reviewing only the effects of the introduction of the partial hierarchy we can see that 100 out of 178 categories see an increase in accuracy.

It should be noted that SARIMA is not part of the test suite. During preliminary testing it came to light that running SARIMA with large seasonal periods proved highly ineffective. While the original goal was to include it in the paper. When running the method early estimates for $m = 24$ showed computation times lasting longer than a week. Combining that with the underlying library, numpy, being able to run out of memory anywhere within that week attempting to utilize SARIMA became futile. An argument could be made that the data could have been made 2-hourly as $m = 12$ could have still shown results. I have chosen to not go down this path as other techniques do manage to attain hourly accuracy, such as MARS and SVR. Utilizing a lower granularity than hourly would not be beneficial as at the writing of this paper modern energy pricing infrastructure, such as EPEX SPOT [22], is at worst hourly based.

8.2 interpretation

From table 1 we can see that the baseline methods themselves already have a high accuracy compared to the ARMA based methods. With their MAPE scores being considerably lower the baseline methods take a strong lead. And while the persistence method falls off when looking at the RMSE score the baseline methods are still of a comparable level to the ARMA based models when looking at the MAE and MRE scores. We can also see that for all methods their MAE score is almost a factor 10-100 larger than their respective MRE score. Indicating that while these models might not be great at predicting the power consumption for a specific time of day their overall energy consumption of the entire day is accurate.

For the partial hierarchy setup, the results are not overly positive. In 24 out of the 88 categories to compete in do the partial hierarchy ARMA based methods win. If we were to assume a standard error margin of $\alpha > 0.05$, the relative score being larger than 5%, only 7 of those wins could be designated as confident wins. Most of which are in the same metric, RMSE. Additionally, the introduction of the partial hierarchy, when ignoring the baseline methods, shows that in 100 out of 178 categories the model leads to a higher accuracy. However, when viewing that through the same error margin only 28 out of 178 categories show a confident positive answer.

8.3 implication

The total results therefore deem ARMA based methods unfit as their baseline counterparts are cheaper to compute and perform at a similar level. Only when looking at a partial hierarchy can some claims of effectiveness be made, if a house has a smart meter in the bedroom the overall accuracy can be increased by taking the bedroom signal and modelling it separately. However, these claims of effectiveness can only be made when looking at one metric. Looking at all four metrics not a single partial hierarchy shows a confident improvement, $\alpha > 0.05$, in more than one of the metrics. Considering that only in 7 of 88 cases a confident improvement over non partially hierarchic methods was achieved. When disregarding the baseline methods, the ARMA based models do see an increase when a partial hierarchy is introduced. However as only 28 of those can be marked as confident improvements it is by far a blanket type of solution that could be applied to any ARMA based model.

8.4 limitations

While a limited amount of success was discovered with the partial hierarchy structure. It is beyond the scope of this paper to compare the partial hierarchy method when combined with different methods. ARMA based methods clearly have a limited benefit from the structure, yet different methods could react in a more positive manner. We should therefore not discard the partial hierarchy structure as a whole. The generalizability of the results is also limited by the choice of metric. We used an error margin of $\alpha > 0.05$ to justify whether a better score was confidently better. However not all metrics behave the same or can be compared this way. One could choose to use the Mean Squared Error, MSE, instead of the RMSE. While these metrics encode the same information, directly comparing two MSE scores to each other will return a different relative score than when comparing two RMSE scores.

9 Conclusions and Future Work

In summary, this paper investigated predicting household energy consumption and attempted to answer the following main question: "Can the forecast accuracy for a single household be improved by using a partial hierarchical structure when using an ARMA based method?" To which the answer was no. With only 28 out of 178 categories leading to a confident positive result this technique should only be applied when you can prove its effectiveness beforehand, it is not suitable as a blanket type of solution. On top of that the SARIMA based method was incapable of being utilized due to long run times. For the other two ARMA based methods certain cases were found in which it would make sense to apply the technique but with the results spread far and with no resounding positive results no positive conclusions could be drawn.

As no appliance could be transformed into a partial hierarchy with a confident improvement, the sub question "What devices, when modelled separately in the hierarchy, lead to the largest improvement of accuracy?" can for now be answered with: none. As baseline techniques such as the seasonal moving average outperformed the ARMA based methods in most scenarios the answer to the final sub question "How do simple persistence methods compare to ARMA based methods?". Can be answered as: simple persistence methods can perform on an equal if not more accurate level than ARMA based methods when it comes to household energy consumption prediction. In the scenarios where an ARMA based method did have the upper hand it only gained a slight increase in accuracy when using the partial hierarchy model, and in most cases this advantage could still fall within a margin of error.

With this paper concluding future avenues of research are to be recommended. The first curiosity is to try another technique that is not directly ARMA based. As ARMA based methods were already not the biggest performers it would make sense to try another technique such as support vector regression. The second recommendation is to mix and match techniques. Using the same technique to model both the separate device as well as the remainder of the house is a naive concept. Certain devices benefit from different models. Those devices which are regular consumers, like a fridge, might benefit from an ARMA method while a model for the TV will be better off with a moving average. My final and most important recommendation is to not limit yourself to one data set. We only considered the New York Pecan Street data set, but it would be interesting to see if other data sets perform better. ARMA based methods are after all still used in the field of energy prediction so it would be useful to see if these results are a fluke of the data set or are more encompassing of the actual world.

This research has shown that while there might still be promise in using a partial hierarchy technique ARMA based methods do not have the capability of sufficiently modelling a household's energy consumption. Both when modelling the total energy consumption of a house as well as when utilizing a partial hierarchy. Further research will be required to see if the partial hierarchy technique can deliver with different algorithms.

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A Section Heading

critic	device	method	partial_hierarchy
mre	bedroom1	ARIMAX	0.0004184252829904985
mre	wellpump1	ARIMAX	0.00014828766148642663
mre	pump1	ARIMA	0.0026498853234476873
mre	circpump1	ARIMAX	0.000579650713600588
mre	garage1	ARIMA	-0.002151999652631072
mre	kitchenapp2	ARIMA	0.01721866330686272
mre	livingroom1	ARIMA	0.012437188609127162
mre	livingroom1	ARIMAX	0.008427139971752063
mre	wellpump1	ARIMA	0.04275254462702738
mre	air1	ARIMAX	0.010570688954377799
mre	kitchenapp1	ARIMAX	0.0043595459208773495
mre	waterheater1	ARIMA	0.06171354090142985
mre	freezer1	ARIMAX	0.010883182196332731
mre	refrigerator1	ARIMAX	0.0057860983735503755
mape	lights_plugs1	ARIMA	97.55032831458911
mre	clotheswasher1	ARIMA	0.036654631158401695
mre	refrigerator1	ARIMA	0.03702766411304275
mape	garage1	ARIMA	398.75773047725846
mre	kitchenapp2	ARIMAX	0.0034548263088910775
mre	freezer1	ARIMA	0.026421075334460916
mape	waterheater1	ARIMA	154.8842096709387
mape	range1	ARIMA	363.62845577425395
mae	livingroom1	ARIMAX	0.20197782359546798
mre	range1	ARIMA	0.03832865205330468
mape	refrigerator1	ARIMA	121.91148104623333
mre	dishwasher1	ARIMA	0.059682429997113894
mape	livingroom1	ARIMAX	111.34785958628838
mape	wellpump1	ARIMA	190.83801483373742

total	relative_difference
-0.0029085184917567817	0.8561380014683131
0.0009109483730079638	0.8372161739564025
0.014374540629758514	0.815654260424724
0.002127056262250327	0.7274868916784812
0.005689609527698554	0.621766723682081
0.03283880332518092	0.4756610605947572
0.021859546702324904	0.43104087296538557
0.01445405123032287	0.4169703816966601
0.061886186317635934	0.30917467740544824
0.01470824331859268	0.28130853390116284
0.006029976075404692	0.27702102523105526
0.0824773890161841	0.2517520057609955
0.013526542959834438	0.19542027636705642
0.007016565467583937	0.17536601058142148
114.81340233222673	0.15035765570020118
0.04293929251549572	0.1463615488034892
0.04214756653814158	0.12147563538373098
451.9537206410985	0.11770229502344022
0.0038412488708845943	0.10059815830275226
0.02866984380832439	0.07843671869640728
168.01275483630303	0.07814016964459418
394.0941177717394	0.07730554865863601
0.2162245447044905	0.06588854715126455
0.04100068012502475	0.06517033531083312
130.20131808780926	0.06366937879987636
0.0636316981392452	0.06206447820218667
118.21341135787175	0.05807760467041287
202.07434728345132	0.05560494244206369

B Full results table

critic	device	method	partial_hierarchy	total
mae	air1	ARIMA	0.36182262264632437	0.3586532619561779
mae	air1	ARIMAX	0.3342810839929785	0.3470072583903209
mae	air1	MA	0.3387053869047619	0.3387053869047619
mae	air1	REPEAT	0.3599795833333333	0.35997958333333335
mape	air1	ARIMA	108.01773012866465	102.93125121426286
mape	air1	ARIMAX	90.28041800390413	93.578531956966
mape	air1	MA	98.1507324321877	98.1507324321877
mape	air1	REPEAT	95.39633261035283	95.39633261035281
mre	air1	ARIMA	0.04931914508422125	0.034088431103016126
mre	air1	ARIMAX	0.010570688954377799	0.01470824331859268
mre	air1	MA	0.0048868303571428535	0.0048868303571428535
mre	air1	REPEAT	0.003350208333333332	0.003350208333333332
rmse	air1	ARIMA	0.5683692185050506	0.5557228878611745
rmse	air1	ARIMAX	0.543214563762088	0.5481319806018589
rmse	air1	MA	0.5508789465007374	0.5508789465007373
rmse	air1	REPEAT	0.6760852963806827	0.6760852963806826
mae	bathroom1	ARIMA	0.3325685261125808	0.3318242808070354
mae	bathroom1	ARIMAX	0.3086245155518625	0.3078533976760848
mae	bathroom1	MA	0.2853070684523809	0.28530706845238096
mae	bathroom1	REPEAT	0.3383893229166667	0.3383893229166667
mape	bathroom1	ARIMA	110.98877076243787	111.06663679880651
mape	bathroom1	ARIMAX	96.99645271639545	96.66045778311103
mape	bathroom1	MA	91.70199234985625	91.70199234985625
mape	bathroom1	REPEAT	102.18913648798132	102.18913648798132
mre	bathroom1	ARIMA	0.055248606414464746	0.05428730569568094
mre	bathroom1	ARIMAX	-0.00020018392335980273	5.039785553791849e-05
mre	bathroom1	MA	0.012753385416666665	0.012753385416666667
mre	bathroom1	REPEAT	0.0046171875	0.0046171875
rmse	bathroom1	ARIMA	0.4899888263535792	0.4896527233289288
rmse	bathroom1	ARIMAX	0.4757752568825443	0.4753029113176407
rmse	bathroom1	MA	0.4538510125619363	0.4538510125619363
rmse	bathroom1	REPEAT	0.6005506621684447	0.6005506621684447
mae	bedroom1	ARIMA	0.3496078488164946	0.3525879151577519
mae	bedroom1	ARIMAX	0.37403123389085524	0.37560711105196176
mae	bedroom1	MA	0.37470189732142856	0.37470189732142856
mae	bedroom1	REPEAT	0.3767631510416666	0.3767631510416666
mape	bedroom1	ARIMA	148.9005991840325	150.17032712162649
mape	bedroom1	ARIMAX	157.7361349141087	156.9995483687846
mape	bedroom1	MA	170.88978719595877	170.88978719595877
mape	bedroom1	REPEAT	147.9960428326	147.9960428326
mre	bedroom1	ARIMA	-0.01841751886054193	-0.015002651993540356
mre	bedroom1	ARIMAX	0.0004184252829904985	-0.0029085184917567817
mre	bedroom1	MA	0.016096800595238093	0.016096800595238093
mre	bedroom1	REPEAT	-0.0007194010416666672	-0.0007194010416666672
rmse	bedroom1	ARIMA	0.6495947252163886	0.6501181253446063
rmse	bedroom1	ARIMAX	0.6681814789017522	0.6708362396487104
rmse	bedroom1	MA	0.6696823977636535	0.6696823977636535
rmse	bedroom1	REPEAT	0.8023140010210165	0.8023140010210165
mae	car1	ARIMA	0.6082276538194651	0.5410847234990287

mae	car1	ARIMAX	0.5219757896035402	0.5047207278424996
mae	car1	MA	0.4822139508928571	0.4822139508928571
mae	car1	REPEAT	0.5365334635416665	0.5365334635416666
mape	car1	ARIMA	283.26866635745586	248.67947932105207
mape	car1	ARIMAX	232.47924649261438	212.95814748873715
mape	car1	MA	192.18008721299285	192.18008721299285
mape	car1	REPEAT	191.66041797119368	191.66041797119368
mre	car1	ARIMA	0.13042072897411278	0.0450941460990404
mre	car1	ARIMAX	0.017229732032309562	-0.006305299190086629
mre	car1	MA	-0.017936495535714296	-0.017936495535714296
mre	car1	REPEAT	0.0017795572916666667	0.0017795572916666667
rmse	car1	ARIMA	1.0515609502634726	0.985801385464232
rmse	car1	ARIMAX	0.9347047908571122	0.9147422837288857
rmse	car1	MA	0.9289501139172088	0.9289501139172087
rmse	car1	REPEAT	1.1873026176814452	1.187302617681445
mae	circpump1	ARIMA	0.4014690076252299	0.402315105609521
mae	circpump1	ARIMAX	0.3402559760160997	0.3397249301113525
mae	circpump1	MA	0.35229774925595236	0.35229774925595236
mae	circpump1	REPEAT	0.3970696614583333	0.39706966145833333
mape	circpump1	ARIMA	308.46984229235323	311.9973461918213
mape	circpump1	ARIMAX	205.0173635150004	207.00157591572497
mape	circpump1	MA	199.58815326363157	199.58815326363154
mape	circpump1	REPEAT	198.854206282218	198.854206282218
mre	circpump1	ARIMA	0.07808321832505326	0.08002496688055925
mre	circpump1	ARIMAX	0.000579650713600588	0.002127056262250327
mre	circpump1	MA	0.0033714471726190515	0.0033714471726190515
mre	circpump1	REPEAT	0.004432421874999999	0.004432421875
rmse	circpump1	ARIMA	0.6017596677220172	0.6007729740149355
rmse	circpump1	ARIMAX	0.5227856526115835	0.5209616940011557
rmse	circpump1	MA	0.5432105126577964	0.5432105126577964
rmse	circpump1	REPEAT	0.6858109074595051	0.6858109074595051
mae	clotheswasher1	ARIMA	0.3517555325988776	0.3544331816966265
mae	clotheswasher1	ARIMAX	0.33164670346966485	0.3314517510025242
mae	clotheswasher1	MA	0.32736922433035726	0.32736922433035714
mae	clotheswasher1	REPEAT	0.36543430989583325	0.36543430989583325
mape	clotheswasher1	ARIMA	290.2806649728631	286.76043988873704
mape	clotheswasher1	ARIMAX	239.66826370703166	239.61081616063456
mape	clotheswasher1	MA	219.3658362207157	219.3658362207156
mape	clotheswasher1	REPEAT	221.17928573221576	221.17928573221582
mre	clotheswasher1	ARIMA	0.036654631158401695	0.04293929251549572
mre	clotheswasher1	ARIMAX	0.011867917774247071	0.008204727825858793
mre	clotheswasher1	MA	0.004370200892857141	0.004370200892857143
mre	clotheswasher1	REPEAT	0.00333671875	0.0033367187499999994
rmse	clotheswasher1	ARIMA	0.5456896092182865	0.5437451432307164
rmse	clotheswasher1	ARIMAX	0.5211425257285265	0.5217629799221675
rmse	clotheswasher1	MA	0.5255604474102769	0.5255604474102769
rmse	clotheswasher1	REPEAT	0.6660149892833822	0.6660149892833822
mae	dishwasher1	ARIMA	0.3547481344199261	0.3559077022474509
mae	dishwasher1	ARIMAX	0.32057154316172237	0.31945301463074244
mae	dishwasher1	MA	0.303394673859127	0.303394673859127

mae	dishwasher1	REPEAT	0.3438483940972222	0.3438483940972221
mape	dishwasher1	ARIMA	167.66268197864113	171.38163260295224
mape	dishwasher1	ARIMAX	126.41073729091596	127.0576175593186
mape	dishwasher1	MA	121.25081368813214	121.25081368813214
mape	dishwasher1	REPEAT	120.549825777903	120.54982577790297
mre	dishwasher1	ARIMA	0.059682429997113894	0.0636316981392452
mre	dishwasher1	ARIMAX	0.015533987160368808	0.012752554772087562
mre	dishwasher1	MA	0.004858413938492062	0.004858413938492063
mre	dishwasher1	REPEAT	0.0030992621527777767	0.003099262152777777
rmse	dishwasher1	ARIMA	0.5396456130238464	0.5379555076344633
rmse	dishwasher1	ARIMAX	0.4984082165786335	0.49904764442942473
rmse	dishwasher1	MA	0.49003304044799406	0.49003304044799406
rmse	dishwasher1	REPEAT	0.6328759188024691	0.6328759188024691
mae	drye1	ARIMA	0.3844607608606396	0.38450542673469423
mae	drye1	ARIMAX	0.3528488717635363	0.36150865449949887
mae	drye1	MA	0.3508530155812326	0.3508530155812325
mae	drye1	REPEAT	0.39147294730392146	0.3914729473039215
mape	drye1	ARIMA	307.2873026347975	298.0987105149925
mape	drye1	ARIMAX	245.4163665429204	251.4481244795929
mape	drye1	MA	225.27491339662132	225.27491339662126
mape	drye1	REPEAT	227.44932188805748	227.4493218880575
mre	drye1	ARIMA	0.046778154809770975	0.0430794361502544
mre	drye1	ARIMAX	0.014957338118510296	0.007076047234030299
mre	drye1	MA	0.00016781775210083775	0.00016781775210083775
mre	drye1	REPEAT	0.0025955575980392163	0.002595557598039216
rmse	drye1	ARIMA	0.6068617860479818	0.5964629270965806
rmse	drye1	ARIMAX	0.5662035340398318	0.5747623882391083
rmse	drye1	MA	0.575172640755863	0.575172640755863
rmse	drye1	REPEAT	0.7301611043102705	0.7301611043102706
mae	freezer1	ARIMA	0.2816691871419735	0.28472239578240977
mae	freezer1	ARIMAX	0.2739537931831323	0.2819768132976373
mae	freezer1	MA	0.26221202168367347	0.2622120216836734
mae	freezer1	REPEAT	0.2858020833333333	0.2858020833333333
mape	freezer1	ARIMA	94.55213717279328	97.86663713084597
mape	freezer1	ARIMAX	86.05679625624967	89.58880675122607
mape	freezer1	MA	93.01331153234743	93.01331153234742
mape	freezer1	REPEAT	91.6497451561352	91.64974515613518
mre	freezer1	ARIMA	0.026421075334460916	0.02866984380832439
mre	freezer1	ARIMAX	0.010883182196332731	0.013526542959834438
mre	freezer1	MA	0.01608115433673469	0.01608115433673469
mre	freezer1	REPEAT	0.004654464285714285	0.004654464285714285
rmse	freezer1	ARIMA	0.45433221811308305	0.4649739341709479
rmse	freezer1	ARIMAX	0.45873946286349215	0.46277934530836545
rmse	freezer1	MA	0.45270195469066693	0.45270195469066704
rmse	freezer1	REPEAT	0.56765539543692	0.56765539543692
mae	furnace1	ARIMA	0.34633952214645514	0.34477232133418406
mae	furnace1	ARIMAX	0.31959044616000043	0.3230665264598013
mae	furnace1	MA	0.31259836985930733	0.31259836985930733
mae	furnace1	REPEAT	0.34327684659090907	0.34327684659090907
mape	furnace1	ARIMA	110.04411848567189	108.98960539628406

mape	furnace1	ARIMAX	92.48636164377359	94.59029589617916
mape	furnace1	MA	94.74386109814205	94.74386109814203
mape	furnace1	REPEAT	93.8487478015334	93.8487478015338
mre	furnace1	ARIMA	0.054337218028832686	0.05024962295228545
mre	furnace1	ARIMAX	0.019606679995119093	0.015724692399210673
mre	furnace1	MA	0.002974519751082252	0.002974519751082252
mre	furnace1	REPEAT	0.0032861268939393933	0.0032861268939393938
rmse	furnace1	ARIMA	0.5390261703863295	0.5366189447672114
rmse	furnace1	ARIMAX	0.511531030753133	0.5157020843306724
rmse	furnace1	MA	0.513231262084142	0.513231262084142
rmse	furnace1	REPEAT	0.6465907194010536	0.6465907194010536
mae	garage1	ARIMA	0.3753963980530926	0.381257389661163
mae	garage1	ARIMAX	0.37816580505351877	0.3771554820625824
mae	garage1	MA	0.34195276360544213	0.3419527636054421
mae	garage1	REPEAT	0.37512053571428566	0.37512053571428566
mape	garage1	ARIMA	398.75773047725846	451.9537206410985
mape	garage1	ARIMAX	419.3750104498814	418.5769384859944
mape	garage1	MA	351.0634451927263	351.06344519272625
mape	garage1	REPEAT	354.0826664621154	354.0826664621155
mre	garage1	ARIMA	-0.002151999652631072	0.005689609527698554
mre	garage1	ARIMAX	-0.004575717906019754	-0.00481045003984089
mre	garage1	MA	-0.0040498299319727945	-0.0040498299319727945
mre	garage1	REPEAT	-0.002999255952380952	-0.0029992559523809516
rmse	garage1	ARIMA	0.6964348747311359	0.6989658176606028
rmse	garage1	ARIMAX	0.6863974294137513	0.6852293910694278
rmse	garage1	MA	0.670167786659602	0.6701677866596022
rmse	garage1	REPEAT	0.8546648354558266	0.8546648354558266
mae	heater1	ARIMA	0.3047157357323949	0.2907116207530493
mae	heater1	ARIMAX	0.2924778967937507	0.28796977995903233
mae	heater1	MA	0.27569081439393944	0.2756908143939394
mae	heater1	REPEAT	0.3045621685606061	0.304562168560606
mape	heater1	ARIMA	141.15501870369644	134.63044666130847
mape	heater1	ARIMAX	128.39079294010537	125.15445587935501
mape	heater1	MA	119.44606868136339	119.44606868136339
mape	heater1	REPEAT	118.50587398545971	118.50587398545973
mre	heater1	ARIMA	0.04572508274771194	0.019211365269974603
mre	heater1	ARIMAX	0.011737602683440096	0.0013185902409134258
mre	heater1	MA	0.007224215367965365	0.0072242153679653665
mre	heater1	REPEAT	0.0028430397727272727	0.0028430397727272727
rmse	heater1	ARIMA	0.48384484093564667	0.46277335021979327
rmse	heater1	ARIMAX	0.47298651028583516	0.4667326814545096
rmse	heater1	MA	0.45919375858693195	0.45919375858693195
rmse	heater1	REPEAT	0.5807839885496677	0.5807839885496677
mae	kitchenapp1	ARIMA	0.3409312620040456	0.3399335256923772
mae	kitchenapp1	ARIMAX	0.32489081828824573	0.3254367485600059
mae	kitchenapp1	MA	0.3011442915013227	0.3011442915013227
mae	kitchenapp1	REPEAT	0.32919618055555544	0.3291961805555555
mape	kitchenapp1	ARIMA	144.99742480560997	143.42324598788093
mape	kitchenapp1	ARIMAX	123.5762659105599	124.76273578355966
mape	kitchenapp1	MA	112.59818743604144	112.59818743604147

mape	kitchenapp1	REPEAT	111.09366169184271	111.09366169184273
mre	kitchenapp1	ARIMA	0.03352129258815286	0.031489311931983094
mre	kitchenapp1	ARIMAX	0.0043595459208773495	0.006029976075404692
mre	kitchenapp1	MA	-0.002466662533068785	-0.0024666625330687854
mre	kitchenapp1	REPEAT	-0.00016660879629629616	-0.00016660879629629607
rmse	kitchenapp1	ARIMA	0.5679862133227952	0.5670722651137793
rmse	kitchenapp1	ARIMAX	0.5536375549394871	0.5539518902313352
rmse	kitchenapp1	MA	0.5409183503691621	0.540918350369162
rmse	kitchenapp1	REPEAT	0.685654155528551	0.6856541555285511
mae	kitchenapp2	ARIMA	0.31322367398425804	0.32387709164337586
mae	kitchenapp2	ARIMAX	0.31002867470299816	0.3103420476874686
mae	kitchenapp2	MA	0.289600923859127	0.28960092385912695
mae	kitchenapp2	REPEAT	0.31803858506944443	0.31803858506944443
mape	kitchenapp2	ARIMA	135.95636683738587	141.58107213245853
mape	kitchenapp2	ARIMAX	118.88496081264448	118.62398821725269
mape	kitchenapp2	MA	110.73022737818877	110.73022737818879
mape	kitchenapp2	REPEAT	106.36688867495377	106.36688867495377
mre	kitchenapp2	ARIMA	0.01721866330686272	0.03283880332518092
mre	kitchenapp2	ARIMAX	0.0034548263088910775	0.003841248870884594З
mre	kitchenapp2	MA	0.003390730406746031	0.0033907304067460307
mre	kitchenapp2	REPEAT	0.001331119791666669	0.001331119791666666
rmse	kitchenapp2	ARIMA	0.5406896179015198	0.5465788282997319
rmse	kitchenapp2	ARIMAX	0.5382379303954626	0.5383734362844251
rmse	kitchenapp2	MA	0.5254446822839935	0.5254446822839935
rmse	kitchenapp2	REPEAT	0.6616049361634991	0.6616049361634991
mae	lights_plugs1	ARIMA	0.3052821870790066	0.3048795821887883
mae	lights_plugs1	ARIMAX	0.26839180301652965	0.26986273688294543
mae	lights_plugs1	MA	0.24423087797619045	0.24423087797619045
mae	lights_plugs1	REPEAT	0.2706220833333333	0.2706220833333334
mape	lights_plugs1	ARIMA	97.55032831458911	114.81340233222673
mape	lights_plugs1	ARIMAX	91.51542961911727	91.89611903149137
mape	lights_plugs1	MA	98.52671198572085	98.52671198572084
mape	lights_plugs1	REPEAT	92.17282140829185	92.17282140829185
mre	lights_plugs1	ARIMA	0.07087946046885579	0.07046819925174899
mre	lights_plugs1	ARIMAX	0.018276057906323	0.0179007978449341
mre	lights_plugs1	MA	0.03219334821428571	0.03219334821428571
mre	lights_plugs1	REPEAT	0.007452499999999999	0.007452499999999999
rmse	lights_plugs1	ARIMA	0.47622316480198534	0.47639271036284525
rmse	lights_plugs1	ARIMAX	0.4447941985742965	0.4476671494542311
rmse	lights_plugs1	MA	0.4236735259305465	0.4236735259305465
rmse	lights_plugs1	REPEAT	0.5504960809735469	0.550496080973547
mae	livingroom1	ARIMA	0.2142628034604186	0.21403613260688872
mae	livingroom1	ARIMAX	0.20197782359546798	0.2162245447044905
mae	livingroom1	MA	0.20149868551587302	0.20149868551587302
mae	livingroom1	REPEAT	0.22467682291666666	0.22467682291666666
mape	livingroom1	ARIMA	122.17318567128272	127.0178730030442
mape	livingroom1	ARIMAX	111.34785958628838	118.21341135787175
mape	livingroom1	MA	119.629142167763	119.629142167763
mape	livingroom1	REPEAT	119.11899811017607	119.1189981101761
mre	livingroom1	ARIMA	0.012437188609127162	0.021859546702324904

mre	livingroom1	ARIMAX	0.008427139971752063	0.01445405123032287
mre	livingroom1	MA	0.0240578125	0.0240578125
mre	livingroom1	REPEAT	0.007370920138888895	0.00737092013888889
rmse	livingroom1	ARIMA	0.34444547789112256	0.33663090053613587
rmse	livingroom1	ARIMAX	0.3339479161417353	0.34409270467922726
rmse	livingroom1	MA	0.3310665034593679	0.3310665034593679
rmse	livingroom1	REPEAT	0.4231897790455739	0.4231897790455739
mae	oven1	ARIMA	0.2283673589404581	0.22309134120102944
mae	oven1	ARIMAX	0.22450891492304934	0.22381597456519783
mae	oven1	MA	0.23701201636904765	0.2370120163690476
mae	oven1	REPEAT	0.2515416666666666	0.2515416666666667
mape	oven1	ARIMA	465.289519565009	430.7962887413043
mape	oven1	ARIMAX	393.4216675898583	394.4331243039478
mape	oven1	MA	344.3674724910664	344.3674724910664
mape	oven1	REPEAT	343.87766293771546	343.87766293771546
mre	oven1	ARIMA	0.005393065222729719	-0.0015474788025299623
mre	oven1	ARIMAX	0.0170213083341667	0.006672677900841268
mre	oven1	MA	0.015058965773809526	0.015058965773809524
mre	oven1	REPEAT	0.0032953125	0.0032953125
rmse	oven1	ARIMA	0.37229324947551934	0.3680622637350468
rmse	oven1	ARIMAX	0.370738895576254	0.3712980723134023
rmse	oven1	MA	0.38637156585194615	0.3863715658519462
rmse	oven1	REPEAT	0.47091915014726365	0.47091915014726365
mae	pump1	ARIMA	0.36082202187462686	0.36297962861288735
mae	pump1	ARIMAX	0.3750350886045563	0.37426224169075195
mae	pump1	MA	0.3868447172619047	0.3868447172619048
mae	pump1	REPEAT	0.41574697916666664	0.4157469791666667
mape	pump1	ARIMA	98.5052618564778	103.46026063612298
mape	pump1	ARIMAX	99.56537096376647	102.2608234256021
mape	pump1	MA	103.03942000941325	103.03942000941325
mape	pump1	REPEAT	96.22989345554258	96.22989345554257
mre	pump1	ARIMA	0.0026498853234476873	0.014374540629758514
mre	pump1	ARIMAX	0.004271849070539746	0.003847941266912666
mre	pump1	MA	0.00161188988095238	0.0016118898809523794
mre	pump1	REPEAT	0.0022686458333333317	0.0022686458333333317
rmse	pump1	ARIMA	0.5493359434218708	0.5492405336334051
rmse	pump1	ARIMAX	0.5627791058399486	0.5670147390775744
rmse	pump1	MA	0.5787143003276786	0.5787143003276786
rmse	pump1	REPEAT	0.6873350869607358	0.6873350869607358
mae	range1	ARIMA	0.38984659648595127	0.39121977903763205
mae	range1	ARIMAX	0.35760535854652603	0.36125269886670675
mae	range1	MA	0.35587122023809525	0.35587122023809525
mae	range1	REPEAT	0.3931813541666666	0.3931813541666666
mape	range1	ARIMA	363.62845577425395	394.0941177717394
mape	range1	ARIMAX	336.5808280299896	337.13551635671126
mape	range1	MA	302.3485409436749	302.3485409436748
mape	range1	REPEAT	309.15285150580996	309.1528515058099
mre	range1	ARIMA	0.03832865205330468	0.04100068012502475
mre	range1	ARIMAX	0.005811120599128345	0.005792433016188748
mre	range1	MA	-0.004884077380952383	-0.004884077380952383

mre	range1	REPEAT	0.002421041666666677	0.002421041666666677
rmse	range1	ARIMA	0.6196977259087006	0.6181177552451161
rmse	range1	ARIMAX	0.5805667299367998	0.5828691020815515
rmse	range1	MA	0.595837799118087	0.5958377991180871
rmse	range1	REPEAT	0.753764357674571	0.753764357674571
mae	refrigerator1	ARIMA	0.3191902910188607	0.3215178443652495
mae	refrigerator1	ARIMAX	0.29716415872262963	0.29674393101316987
mae	refrigerator1	MA	0.3097538256448412	0.3097538256448413
mae	refrigerator1	REPEAT	0.33856050347222216	0.3385605034722221
mape	refrigerator1	ARIMA	121.91148104623333	130.20131808780926
mape	refrigerator1	ARIMAX	104.29937731058925	107.55184268601751
mape	refrigerator1	MA	118.23236919999363	118.23236919999361
mape	refrigerator1	REPEAT	114.17788706486617	114.17788706486617
mre	refrigerator1	ARIMA	0.03702766411304275	0.04214756653814158
mre	refrigerator1	ARIMAX	0.0057860983735503755	0.007016565467583937
mre	refrigerator1	MA	0.016701271081349205	0.016701271081349205
mre	refrigerator1	REPEAT	0.00623298611111111	0.006232986111111109
rmse	refrigerator1	ARIMA	0.48580630069626024	0.48822012669234827
rmse	refrigerator1	ARIMAX	0.46283917714146794	0.4625588142739044
rmse	refrigerator1	MA	0.47641601604172257	0.47641601604172257
rmse	refrigerator1	REPEAT	0.5927263154151455	0.5927263154151455
mae	waterheater1	ARIMA	0.44222866749547746	0.45780940276176035
mae	waterheater1	ARIMAX	0.4053357675042844	0.41188607580872383
mae	waterheater1	MA	0.40186868303571427	0.4018686830357142
mae	waterheater1	REPEAT	0.45186953124999996	0.45186953124999996
mape	waterheater1	ARIMA	154.8842096709387	168.01275483630303
mape	waterheater1	ARIMAX	126.54529794144551	128.897144958684
mape	waterheater1	MA	131.1049492957628	131.1049492957628
mape	waterheater1	REPEAT	130.874193448217	130.87419344821703
mre	waterheater1	ARIMA	0.06171354090142985	0.0824773890161841
mre	waterheater1	ARIMAX	0.011013290700782007	0.006208153458328934
mre	waterheater1	MA	0.011321063988095232	0.011321063988095232
mre	waterheater1	REPEAT	0.00917234375	0.009172343749999999
rmse	waterheater1	ARIMA	0.6869006795990535	0.7025550445219174
rmse	waterheater1	ARIMAX	0.6464242365310905	0.654798330779141
rmse	waterheater1	MA	0.6596921755580331	0.6596921755580333
rmse	waterheater1	REPEAT	0.8386959674354946	0.8386959674354946
mae	wellpump1	ARIMA	0.4085667383033036	0.4196040466199461
mae	wellpump1	ARIMAX	0.3890831705811355	0.3899877909119762
mae	wellpump1	MA	0.37362493386243384	0.37362493386243384
mae	wellpump1	REPEAT	0.417652025462963	0.41765202546296293
mape	wellpump1	ARIMA	190.83801483373742	202.07434728345132
mape	wellpump1	ARIMAX	162.42836442414352	163.7461537236053
mape	wellpump1	MA	156.33038104299033	156.33038104299033
mape	wellpump1	REPEAT	159.78029902644047	159.78029902644045
mre	wellpump1	ARIMA	0.04275254462702738	0.061886186317635934
mre	wellpump1	ARIMAX	0.00014828766148642663	0.0009109483730079638
mre	wellpump1	MA	0.002359937169312164	0.0023599371693121644
mre	wellpump1	REPEAT	0.005408738425925925	0.0054087384259259245
rmse	wellpump1	ARIMA	0.6378882032497423	0.6508648663555735

rmse	wellpump1	ARIMAX	0.6194043374941536	0.620240217161558
rmse	wellpump1	MA	0.6192768799535874	0.6192768799535875
rmse	wellpump1	REPEAT	0.7822807976656136	0.7822807976656135