Forecasting Electricity Usage in Industrial Applications with GPU Acceleration through RAPIDS AI Framework

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Abstract— **Electricity usage prediction is important for planning and facility expansion in the industrial sector. Accurate prediction can save the operation and maintenance costs, increased the reliability of power supply and delivery system for future development. This paper is to compare various Exponential Smoothing models (Simple Exponential Smoothing, Holt Linear Trend, Holt Linear Damped Trend and Holt-Winters) and ARIMA (Autoregressive Integrated Moving Average) model in an attempt to predict the daily electricity usage in the industry in the production of Hammer and Pellet with high accuracy. The data used is from 30 September 2019 to 06 November 2019, which consist of only 39 observations after excluding the non-production day. These models are precise and modelled well when the time series data is in a short period and in short period forecasting. Accuracy level of each model is measured by comparing the Root Mean Square Error (RMSE) of forecasting value with the actual value. Based on the comparison result, the best model with the smallest RMSE value is given by Holt Linear Trend for the electricity usage for the production of Hammer (in Mill 1 and Mill 2) and the production of Pellet (in Mill 1). In the data of the electricity usage for the production of Pellet (in Mill 2), the smallest RMSE value is given by Holt Linear Damped Trend. To improve the training and forecasting speed, we adopt Graphics Processing Unit (GPU) acceleration through RAPIDS Artificial Intelligence framework.**

Keywords-component; Electricity Consumption Forecasting; Simple Exponential Smoothing; Holt Linear Trend; Holt Linear Damped Trend; Holt-Winters; Auto Regressive Integrated Moving Average.

I. INTRODUCTION

An increase in the consumption of domestic electrical current will cause higher utility costs. An accurate prediction of the future electricity usage in short-run and long-run may help the manufacturing industries and private investors to maximize their return and minimize the operation expenses [1][2]. Forecasting of electricity usage also helps the industry to plan and control on the future power system. Building an accurate and reliable forecasting model for electricity usage may provide valuable information for electricity system operators to formulate policies and plans for electricity [3]. Therefore, forecasting of electricity usage has become urgent and important for an industry [4]-[6].

There are many factors affecting the prediction accuracy of electricity consumption, such as economic condition [7], power facilities [8], population growth [9], weather conditions [10][11], festival season [12] and political influences [13]. Thus, forecasting on the electricity usage become challenges as the data often presents to be strongly nonlinear, random, more volatile and irregular [14]. It is due to the average yearly growth factor of electricity usage fluctuation. Also, the demand of it can change significantly in space and time related to different areas. Therefore, the long-run prediction of electricity usage may be impractical. The accuracy of the prediction in short-run can be improved by select a forecasting model that performs well with a relatively small sample size [14]. Apart from that, it has been found that making full use of more recent data which is closer to the forecast period is able to enhance the prediction performance [15].

Many researchers proposed different kinds of forecast models to predict the electricity usage in recent decades. The methods could be completely categorized into three groups: statistical analysis models, artificial intelligence models and grey forecasting models. Examples of the popular statistical analysis models include regression [16], logistic regression [6], simple Exponential Smoothing model [17][18], Holt-Winters model [19], univariate time series model [9][20], state space model [21], Kalman filter model [3] and Markov chain model [22]. However, statistical analysis models have some limitations, one of that is statistical models usually require that the sample data fulfil some statistical assumptions, such as normality assumption, thus limiting it practical application.

Artificial intelligence models such as artificial neural network [23][24], support vector machine regression [25][26] and deep neural networks [27] become popular in electricity consumption prediction. However, the prediction precision obtained from these models is totally rely on the number of the training sample data [4][28][29], which may not be applied in electricity usage data when the sample size is small.

There are different forecasting approaches including trend and seasonality and several comparative studies in the electricity consumption in the literature. Al-Ghandoor et al. [30] presented the electricity consumption of the Jordanian industrial sector based on multivariate linear regression. In the study, they found that industrial production outputs and capacity utilization are the two important reasons that affect demand on electrical power. Erdogdu [31] used

Autoregressive Integrated Moving Average (ARIMA) to estimate and predict the Turkish electricity demand. Taylor [32] found that Exponential Smoothing method is more reliable and appropriate for short period forecasting on electric consumption. Kavanagh [36] proposed double seasonal Exponential Smoothing variation of the Holt-Winters method to predict the short-term electricity loads for half hourly lead times for a day ahead.

The objective of this project is to compare various statistical approaches to forecast the electricity consumption of a factory. Such comparisons are crucial for the stake holder of the factory to factor in their operation cost in order to maximize production output and minimize production cost. The novelty of this work is to compare various statistical models to investigate the accuracy versus performance of these techniques especially with GPU acceleration. In order to achieve objectively compare the accuracy between the models, external factors such as weather and economic conditions will not be included in this study. This work is a subcomponent to our meta-predictor where accuracy and performance are important factors for the meta-predictor to autonomously select and combine predictions from multiple models.

In this paper, we proposed to use variety of linear models to find the best fitting to predict the future electricity consumption. The linear models that studied in this paper are Simple Exponential Smoothing model, Holt's Linear model, Holt's Linear Damped Trend model, Holt-Winters model, and ARIMA models. Electrical consumption forecasting classified into three categories: short period, medium period and long period. In this study, we focus on 5 working days; that is short term load forecasting. The data is collected from life current sensor transmitted to the cloud hosted for forecast processing. The training and forecasting are accelerated through GPU to achieve better speed performance with similar accuracy.

The paper is organized as follows. In Section II, it provides a review of methodology related works. In Section III, it briefly discusses experiments and performance results. Finally, Section IV concludes and discusses future work.

II. MEHTODOLOGY

A. Methods

We presented in here five approaches for forecasting the electricity consumption. Techniques chosen for this study are Simple Exponential Smoothing model, Holt's Linear model, Holt's Linear Damped Trend model, Holt-Winters Additive model, and ARIMA model. The details of the methods are discussed as following:

1) Simple Exponential Smoothing (ES) model

Exponential Smoothing (ES) is one of the generally used methods to discover the short-term dramatic changes in time series based on its past values. ES model is simple to estimate as it only requires a single parameter, which is the smoothing called as smoothing coefficient. Second, this model required less computational time and small data storage. The simple ES can be represented by the following equations:

$$R_t = \alpha y_t + (1-\alpha) R_{t-1}, \tag{1}$$

$$\hat{y}_t = R_{t-1}, \tag{2}$$

where R_t is the level at time *t*, α is the smoothing constant and $0 < \alpha \leq 1$.

2) Holt's Linear (HL) Model

Double ES is an extension to simple ES as the simple' ES approach does not fit well in the data when there is a trend. The double ES model is formed by two equations:

$$R_t = \alpha y_t + (1-\alpha)(R_{t-1} + c_{t-1}), 0 \leq \alpha \leq 1 \tag{3}$$

$$c_t = \gamma (R_t - R_{t-1}) + (1-\gamma) c_{t-1},\ 0 \leq \gamma \leq 1 \tag{4}$$

where R_t is the level at time *t*, α is the weight for the level, c_t is the trend at time *t*, γ is the weight for the trend, y_t is the data value at time *t*. The one-step-ahead forecast at time *t* is given as

$$\hat{y}_t = R_{t-1} + c_{t-1} \tag{5}$$

Holt's Linear Trend (HLT) is a special case of double ES model with the forecast equation is given as

$$\hat{y}_t = R_{t-1} + h c_{t-1} \tag{6}$$

where *h* is the *h*-step-ahead forecast. However, when the data is with trend and seasonal, HLT may not be performed well, so HLT approach was extended to Holt-Winters method, which can help to measure strong trend patterns and seasonal pattern in the series.

3) Holt's Linear Damped Trend (HLDT) model

Holt's Linear Damped Trend (HLDT) includes a damping parameter, ϕ, where $0 < \phi < 1$. The equation is given as

$$\hat{y}_t = R_{t-1} + c_{t-1}\left(\phi + \phi^2 + \ldots + \phi^h\right) \tag{7}$$

$$R_t = \alpha y_t + (1-\alpha)(R_{t-1} + \phi c_{t-1}),\ 0 \leq \alpha \leq 1 \tag{8}$$

$$c_t = \gamma (R_t - R_{t-1}) + (1-\gamma) \phi c_{t-1},\ 0 \leq \gamma \leq 1 \tag{9}$$

where R_t is the level at time *t*, α is the weight for the level, c_t is the trend at time *t*, γ is the weight for the trend, y_t is the data value at time *t,* and $\hat{y}_t$ is the one-step-ahead forecast at time *t*. If $\phi = 1$, the method is identical to HLT method. The short term forecasts for HLDT method are trended while the long-term forecasts are constant.

4) Holt-Winters (HW) method

The HW method, which is also called triple ES method, is a complex expansion of ES method and is used when there is trend and seasonality in the data set. HW additive method is chosen when the seasonal variations are roughly constant meanwhile HW multiplicative method is chosen when the seasonal variations are changing proportionally to the level of the data. This study will be applied only to the HW additive model:

$$\hat{y}_t = R_{t-1} + hc_{t-1} + s_{t-1} \tag{10}$$

$$R_t = \alpha(y_t - s_{t-p}) + (1-\alpha)(R_{t-1} + c_{t-1}) \tag{11}$$

$$c_t = \beta(R_t - R_{t-1}) + (1-\beta)c_{t-1} \tag{12}$$

$$s_t = \gamma(y_t - R_t) + (1-\gamma)s_{t-p} \tag{13}$$

where R_t is the smoothed estimate of the level at time t, c_t is the smoothed estimate of the change in the trend value at time t, s_t is the smoothed estimate of the appropriate seasonal component at t, α , β and γ are the smoothing parameters and p is the number of seasons per year as in eq. (13).

5) ARIMA Model

The ARIMA model consists of autoregressive (AR) part, a differencing (I) part and Moving Average (MA) part. The ARIMA (p,d,q) model can be expressed in a very general form:

$$(1-B)^d y_t = \vartheta_0 + \alpha_1(1-B)^d y_{t-1} + \ldots + \alpha_p(1-B)^d y_{t-p} + a_t - \theta_1 a_{t-1} - \ldots - \theta_q a_{t-q} \tag{13}$$

where B is the backward operator, ϑ_0 is the constant term, α_i is the AR coefficient, d is the order of the differencing, θ_j is the MA coefficient, where $j = 1,2,\ldots,q$, y_t is the data value at time t, and a_{t-q} is the random noise, which follows normal distribution. In this model, α_1 , α_2 ,…, α_p , ϑ_0 and θ_1 , θ_2 ,…, θ_p are optimised by using maximum Likelihood Estimation (MLE) [37]. The best model is selected based on the Box-Jenkins methodology, which is composed of four main stages: model identification, parameter estimation, diagnostic checking and model application [37]. The stationary and invertibility conditions for the selected models should be fulfilled when fitting ARIMA model [38].

B. GPU Acceleration

The training and forecasting process can be time consuming when the data size is large; GPU can be used to accelerate these processes. In this paper, we adopt the RAPIDS AI framework that provides a series of libraries to accelerate machine learning techniques through GPU. These python based libraries use NVIDIA CUDA® primitives for low-level compute optimization. It scrutinizes the data parallelism with adopting high-bandwidth memory. Figure 1 shows the high-level architecture of RAPIDS.

In particular, we use cuDF, which is CUDA dataframe. This is a powerful data representation layer. It contains pandas-like functionalities for low level CPU and GPU components performing a heterogenous parallel computing. It eases up data scientists to manipulate data input/output, mimicking the CPU version of dataframe. On the other hand, we also use cuML, which is a GPU Machine Learning Algorithms library. It comes with Holt-Winter implementation in GPU.

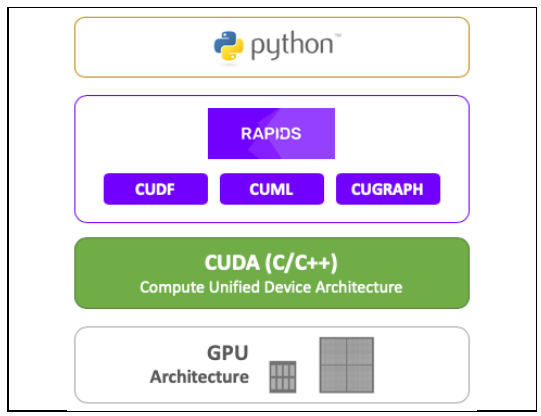

Figure 1. High level of RAPIDS AI architecture framework

C. Forecasting and Performance Accuracy

The static forecasting will be carried out for the next 5 working days. The performance of accuracy in forecasting will be investigated by root mean square error (RMSE) [37], which is shown as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{14}$$

where y_i and $\hat{y}_i$ are the observed and predicted values at time t respectively. The models with the lowest scoring from the four methods will be the best forecast models and can be used for control purpose in future.

III. Results and Discussion

The dataset used in this study is collected from a real plastic molding factory with 4 different milling machines. These are newly purchased machines, as a result, these 2 months historical records are not extensive enough. There are four sets of the data containing 39 observations (from 30-09-2019 till 06-11-2019) of the total electricity load for the production of Hammer and Pellet in Mill 1 and Mill 2. NVIDIA P100 GPU was used for the evaluation, which has 16GB GDDR5 RAM with CUDA version 10.2.

In this study, the data with same electricity consumption is removed. Then the last five observations of these four series are used for forecasting and the rest of the observations formed the training data for parameter estimation. This section mainly demonstrates the prediction process and parameter estimates of the five models, simple ES, HLT, HLDT, HW, and ARIMA and the fitting data. We implement a batch version of trustworthiness that provides reasonable low execution times for dataset up to 39 observations. In addition, after the fitting results are obtained, the accuracy of the five models is analysed and compared with the original data. Figure 2 shows plots of these four series in daily usage and the plots show that trend and seasonality exist.

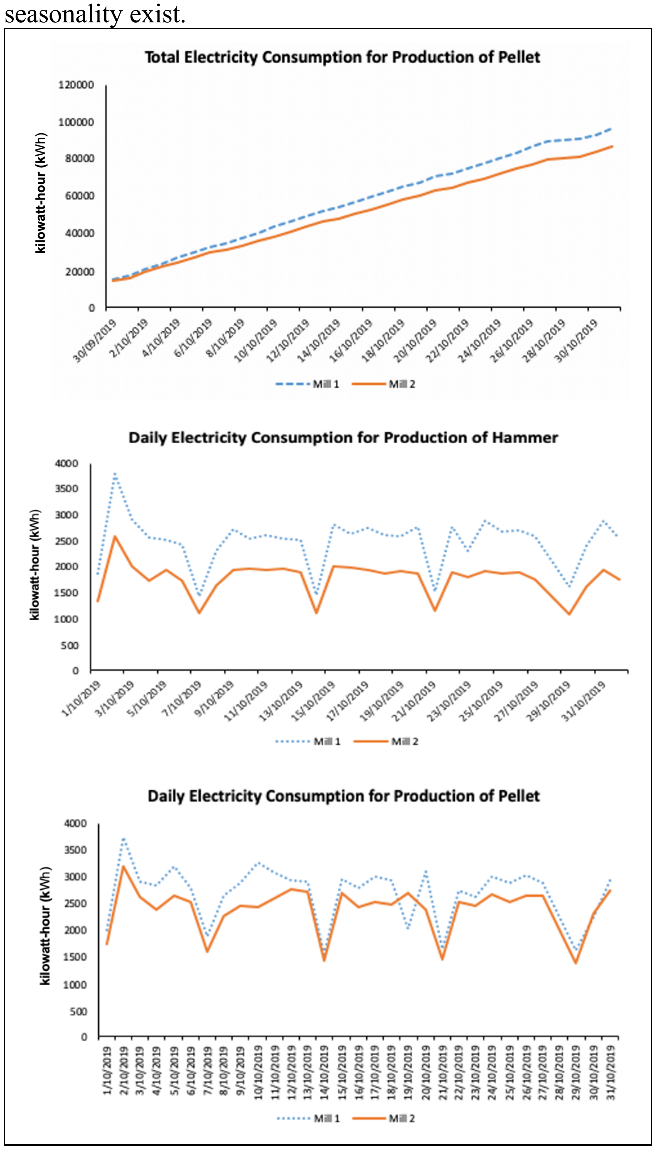

Figure 2. Daily data of the electricity load (in kWh) for the production of Hammer and Pellet in Mill 1 and Mill 2 in the period 01/10/2019 - 30/10/2019.

TABLE I. DAILY ELECTRICITY CONSUMPTION ESTIMATION OUTPUTS OF ES METHODS FOR PRODUCTION OF HAMMER.

	Mill 1				Mill 2			
ES models / Parameters	Single ES	HLT	HLDT	HW-Additive	Single ES	HLT	HLDT	HW-Additive
Alpha	0.9990	1.0	1.0	0.05264	1.0	1.0	1.0	0.05264
Beta	-	0.1	0.1	0.05264	-	0.1	0.1	0.05264
Gamma	-	-	-	0.9474	-	-	-	0.9474
Phi	-	-	0.9973	-	-	-	0.9955	-
Sum of Square Error	1.9364e+08	1.5050e+07	1.0969e+07	2.6639e+06	9.8410e+07	7.0899e+06	4.9372e+06	961291

TABLE II. DAILY ELECTRICITY CONSUMPTION ESTIMATION OUTPUTS OF ES METHODS FOR PRODUCTION OF PELLET.

	Mill 1				Mill 2			
ES models / Parameters	Single ES	HLT	HLDT	HW-Additive	Single ES	HLT	HLDT	HW-Additive
Alpha	1	1	1	0.05263	1	0.9	0.9	0.05263
Beta	-	0.1	0.1	0.05264	-	0.2	0.2	0.05263
Gamma	-	-	-	0.7895	-	-	-	0.8947
Phi	-	-	0.9959	-	-	-	10.9999	-
Sum of Square Error	2.2676e+08	1.7594e+07	8.5834e+06	3.9511e+06	1.7782e+08	1.3128e+07	1.0064e+07	1.6888e+06

For the various implemented models, we briefly illustrate the finding here. TABLES I-II present the estimation outputs of simple ES, HLT, HLDT and HW for the daily electricity consumption of the production of Hammer and Pellet in Mill 1 and Mill 2 respectively. The values of the sum of square errors shown in the TABLE I-II are used to identify the dispersion of the training data in the fitted model. TABLE III presents the ARIMA models that fitted to the four series, the models are selected based on minimum values of Akaike Information Criterion. The performance of accuracy in the forecasting is shown in TABLE IV. From the TABLE IV, it can be seen that the RMSE values of the HLT model are smaller than the ARIMA model and others ES models in the series of Hammer (Mill 1 and Mill 2) and Pellet (Mill 1), and HLDT is the smallest for Pellet (Mill 2). In other words, ES model, HL and HLDT models are more precise in predicting the electricity consumption total data in the production of Hammer and Pellet in Mill 1 and Mill 2.

TABLE III. ARIMA models with its' sum of square error (bracket) for the daily electricity consumption.

	Hammer	Pellet
Mill 1	ARIMA(6,1,0)	ARIMA(6,1,2)
Mill 2	ARIMA(6,1,1)	ARIMA(2,0,0)

	Hammer	Pellet
Mill 1	ARIMA(6,1,0) (1.09166e+05)	ARIMA(6,1,2) (4.2045e+04)
Mill 2	ARIMA(6,1,1) (1.70421e+05)	ARIMA(2,0,0) (1.84790e+05)

TABLE IV. THE RMSE OF THE ARIMA AND ES MODELS.

	Mill 1		Mill 2	
Models	Hammer	Pellet	Hammer	Pellet
Single ES	8126.87	9071.80	5853.39	7877.87
HLT	123.00	500.95	174.33	76.20
HLDT	132.30	745.45	279.14	51.02
HW-Additive	512.38	656.76	387.28	512.38
ARIMA	369.59	721.54	606.60	586.19

GPU computing is at a tipping point, as we compare the execution time and correctness of GPU many-core and CPU implementation against CPU multicore. TABLE V shows the timing performance of CPU and GPU implementation. CPU implementation is provided by statmodels library, while GPU implementation is adopted from cuML. The GPU performance is shown in brackets. We can observe that the GPU can provide around 3× performance improvement in training and forecasting, compared to the CPU implementation. The result turns out that it cannot take full advantages of all the available CUDA cores on the GPU device. The dataset size is too small.

TABLE V. THE TRAINING AND FORECASTING TIME COMPARISON (MS), CPU VS GPU (BRACKET).

	Mill 1		Mill 2	
Models	Hammer	Pellet	Hammer	Pellet
Single ES	69.5 (24.3)	71.5 (23.3)	59.6 (21.0)	69.2 (22.8)
HLT	69.1 (22.2)	72.7 (22.3)	60.5 (23.8)	71.5 (24.1)
HLDT	68.5 (23.1)	70.5 (22.9)	62.4 (21.9)	68.3 (28.2)
HW-Additive	68.7 (22.3)	71.5 (23.8)	69.1 (22.3)	70.2 (24.9)

IV. CONCLUSION

This study aims to compare various ES models and ARIMA model based on RMSE criteria in forecasting the daily electricity usage total data in the industry. From the results of data analysis that has been done, it was found that the model of Holt's Linear with lowest RMSE is the most appropriate model in forecasting the daily electricity usage total data in the production of Hammer (in Mill 1 and Mill 2) and the production of Pellet (in Mill 1). Holt's Linear Damped Trend model gave the lowest RMSE in the production of Pellet in Mill 2. These models are more appropriate when compared with Holt-Winters Additive model and ARIMA model. GPU acceleration is also useful to speed up the training and forecasting with approximately 3× performance gain. However, our experiment shows that there is approximately 40 milliseconds speed up. It is not a significant result, as the current dataset is small. Thus, it requires more new sensors to be used for collecting bigger historical dataset, then, it will be worthwhile from GPU acceleration. For future work, external factors that possibly affecting electricity consumption should also be included and more technique will be included.

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