

Energy consumption prediction for electric rickshaw based on load variance

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Abstract. Electrical Rikshaw forecasting is usually a univariate time series forecasting problem. The recent increase in load variance of electric rickshaw has lead to large available datasets. In this case, we use the machine learning approach based on Long Short Term Memory (LSTM) and Support Vector Machine (SVM). The accurate energy consumption of electric Rickshaw forecasting is depended to train and test real dataset. The time series of electric Rickshaw observed in Mechanical Labs of Universitas HKBP Nomensen, Medan, Indonesia. The main aim of this paper to generate the observation of energy consumption from the electric rickshaw and look for accuracy of electrical load in the substation.

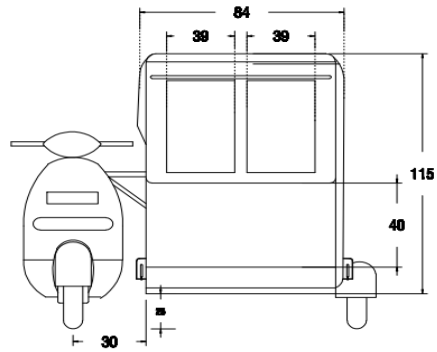
1. Introduction

In many general time series forecasting models or methods can be applied for energy consumption forecasting[1]. As we know the problem of power demand forecasting in an electric rickshaw is important to look at the performance based on the load variance. This paper explores Long Short Term Memory (LSTM) and Support Vector Machine as the Machine learning techniques to look at the performance of electric rickshaw for energy consumption and accuracy based on load variance. Machine learning approaches are proving useful for electric rickshaw on energy consumption forecasting[2][3]–[6]. The physical of the load variance on the electric rickshaw is depend on distance and weight[7]. The goal of this paper to evaluate the performance of electric rickshaw based on the energy consumption in load variance using the LSTM and SVM.

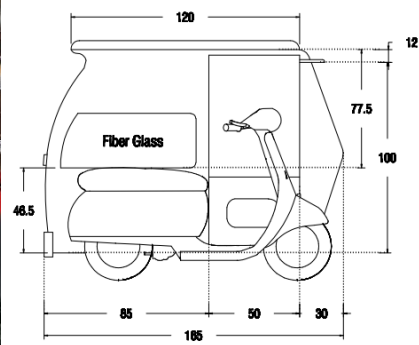
2. Data and Method

2.1 Data

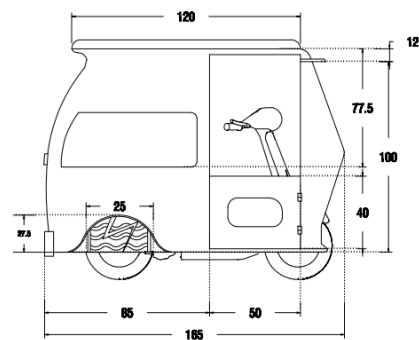
The data were employed in the Nomensen University Labs, which recorded from an electric rickshaw in Fig.1. The observation was testing with different weight, time and constant velocity.



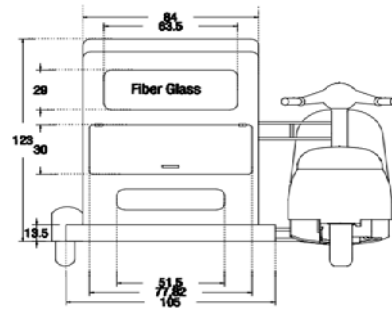
(a)front view image



(b) right side view image



(c)Left side view image



(d)Right Side view Image



(e)Testing with a load of 0 Kg (f)Testing with a load of 60 Kg(g)Testing with a load of 170 Kg

Figure 1. Electric rickshaw

In this paper, the tests are carried out on flat road conditions. The rickshaw body weights about 80 kg. the battery life normal condition is 600-800 cycles. In table 1, showing the testing in 0 kg with a constant velocity of 20 Km/hour. The battery life condition was change starting from time and different distance.

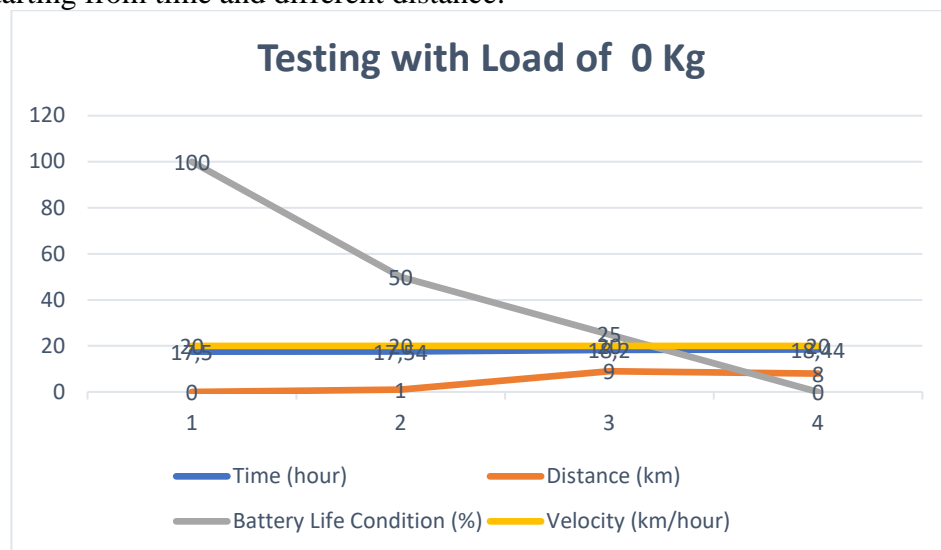


Figure 2. Testing with a load of 0 Kg

In Fig.2 shows the testing of a rickshaw with a load of 0 Kg, the testing with normal velocity condition 20 Km/hour, with total distance 31 Km and amount of time in this testing 114 minutes. Fig.2 shows the dataset in a load of 60 Kg, with normal velocity 25 Km/hour, the total distance 1 in this testing 17 Km and the amount of time in this experiment is 54 minutes.

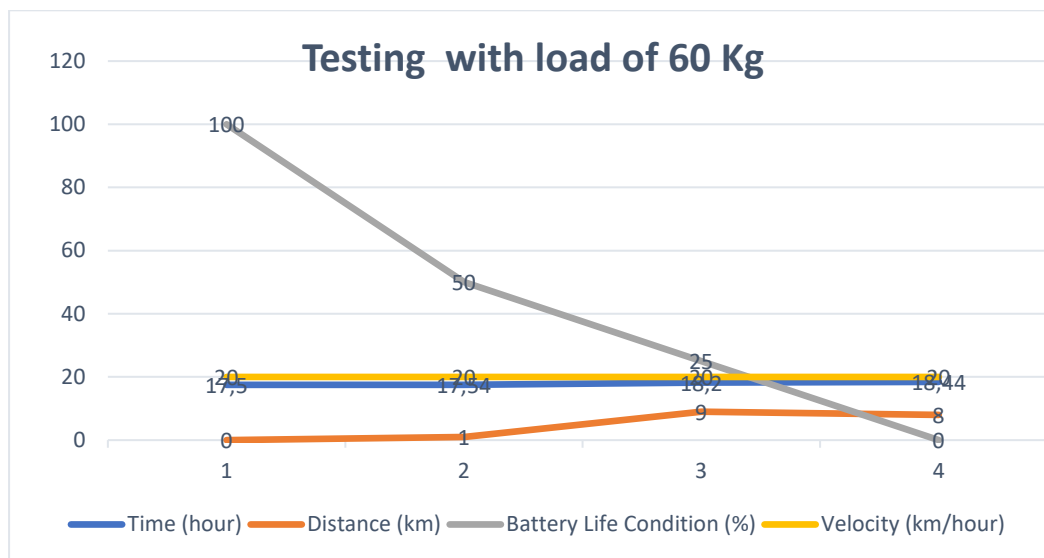


Figure 3. Testing with a load of 60 Kg

The performance in Fig.3 shows that after the condition of the battery decreases with speed in normally, but in this case, the distance in 5 Km the performance of battery life condition will be normal in 50 %.

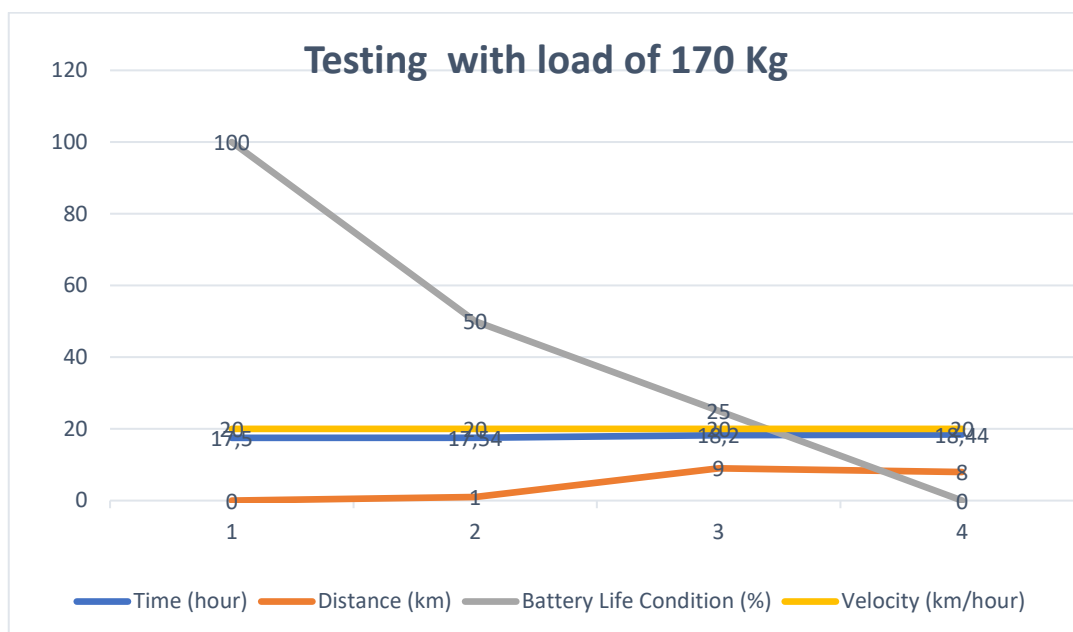


Figure 4. Testing with a load of 170 Kg

In Fig.4 show that the variance load does not greatly affect the life condition of the battery, but with normal velocity in 20 Km, there was variance condition in the change of distance. The amount of time in third testing is 50 minute, with a total distance of 18 Km.

2.2Method

This research area using the LSTM and SVM are included in the literature about load forecasting [8]. The important element of energy consumption forecasting is finding the relationship between input variables and forecasting parameter. The SVM can be used for classification and regression task. In this case, we used regression by approach the support vector regression[9][10]. The optimization problems in SVR does not have any feasible solution, a tolerance parameter on the threshold is introduced. The long Short Term Memory networks are a particular class of recurrent ANNs where the neuron in the hidden layers are replaced by the so-called memory cells (MC). An MC is a particular structure that allows storing information about past network states[8], [11].

3. Result and Discussions

In this section, we briefly describe the considered machine learning techniques by adopted forecasting by using LSTM and SVM to perform the power forecasts with electric rickshaw. The characteristics of testing include time, Battery condition and time series of testing as shown in figure 5.

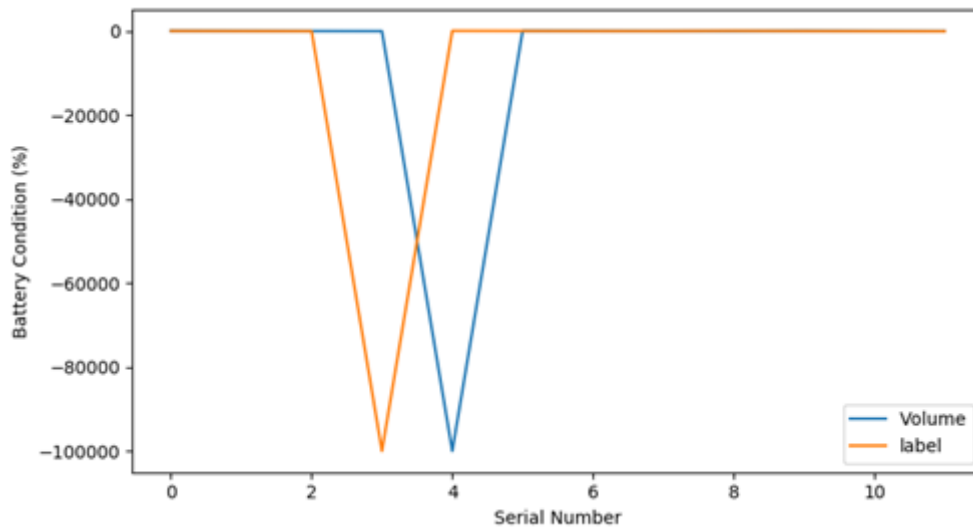


Figure 5. Energy consumption prediction based on SVM

Fig. 5 shows the mean absolute error of the forecasts obtained by the SVM model. The train score for SVM approach 22.33 % RMSE, the Test Score is 38.25 % RMSE with accuracy 64.269219 %. The prediction in Fig.1 shows that the blue line is Battery Life Condition in train score, and the orange line is test score predicts.

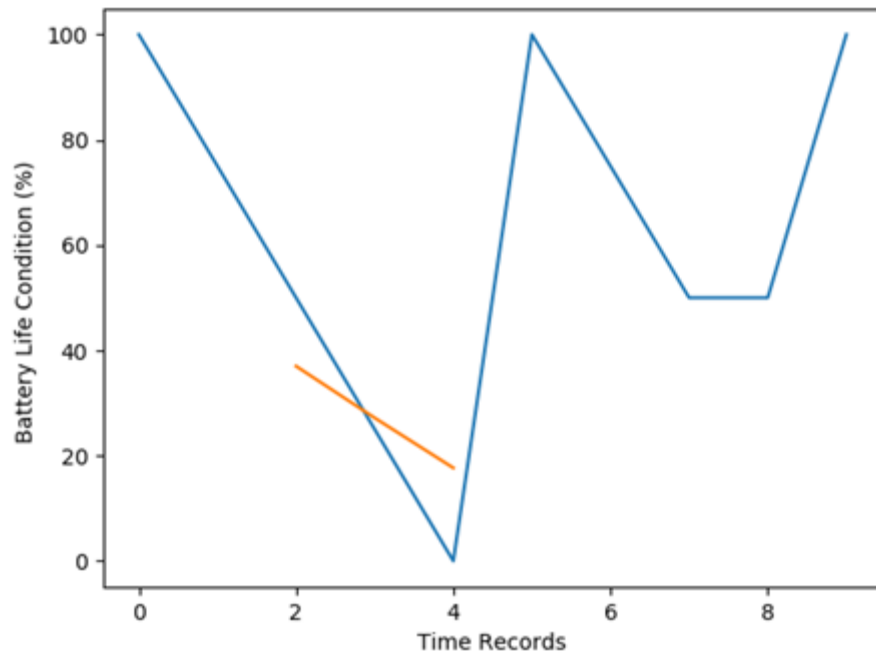


Figure 6. Energy consumption based on LSTM

The result of the LSTM approach in Fig.6 shows the accuracy of the model is 76.389052 %, and train score 14.76 RMSE. The test score in LSTM 23.42 RMSE.

4. Conclusions

Based on the results obtained in the study, the LSTM and SVM are proving useful for energy consumption forecasting. The performance of different machine learning approaches in terms of SVM and LSTM. The LSTM prediction accuracy concerning others, but the smallest error variance. The resulting point both of machine learning technique based on LSTM and SVM are a possibility for analysis experiment data for such purposes.

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