# Estimation of Remaining Range of Electric Vehicle using Kalman Filter

Shailesh S. Sonalikar
Dept. of Production Engineering and Industrial Management
College of Engineering Pune
Pune, India
sonalikarss16.mecha@coep.ac.in

Sushama D. Shelke
E&TC Department
Dr. D. Y. Patil Institute of Engineering, Management and Research, Pune, India
shelke.sushama@gmail.com

***Abstract*—Electric vehicles have a limited driving range compared to conventional vehicles. Running out of battery energy is same as breakdown. The charging times for the EVs are also significant. Hence it is important to accurately indicate the driving range of the vehicle to the driver. In this paper a simple approach to calculate the real time driving range of the EV using Kalman estimation is implemented. Kalman filter try to provide a better estimation of the energy consumption considering the nonlinear nature of the vehicle energy consumption and noise in the measurement.**

***Keywords— Remaining driving range, Distance to Empty, Electric Vehicles, Kalman Filter***

## I. INTRODUCTION

Now a day's electric vehicles are coming up as better and cleaner alternative for conventional vehicles. Many automotive manufacturers are shifting towards green technology. Electric Vehicles still face many hurdles like limited battery storage capacity, limited driving range, long charging cycles.

Range anxiety is one of the reason customers are reluctant to go for EV. The driver is anxious whether he will reach the destination or not before the battery drains completely. Hence providing an accurate and reliable indication of vehicle's range with available battery capacity is very important. Remaining Range is affected by available battery capacity, energy consumption, driving pattern.

Factors that directly affect energy consumption are speed, acceleration, load, number of passengers, road inclination, traffic, auxiliary electric loads, temperature.

All these factors affecting energy consumption indirectly affects the EV range. Hence accurate estimation of energy consumption is most important step in determining Remaining Range. Many range estimation algorithms use a static value of watt hour per kilometer to calculate the range. Some use nonlinear model of the battery to incorporate dynamics of battery along with physics based EV model to obtain the energy requirement for specific speed and acceleration [1][2]. Data driven and statistical approaches are also being investigated such as regression and machine learning [3][4]. Some approaches include future driving profile prediction and traffic condition prediction [2][3]. Such approach can estimate the range with good accuracy only when the data of future route, road, traffic, inclination is available in advance, which is not the case every time.

Here a simple approach is followed using Kalman filter and real time vehicle data such as speed, acceleration, state of charge, distance, battery current and voltage. The Kalman filter estimates the real time energy consumption of the EV which is then used to calculate the range.

The rest of this paper is organized as follows: section II introduces the Kalman filter as estimator and state space plant model of the electric bus; section III describes the estimation of energy consumption using Kalman Filter. In section IV, range estimation and related terms are described. Section V shows results of the research; and section VI concludes the paper and explains the future scope.

## II. METHODOLOGY

### *A. Kalman Filter as Estimator*

By definition Kalman filtering is an iterative mathematical process that uses a set of equations and consecutive data inputs to quickly estimate the true value of the object being measured, when the measured value contains unpredicted or random error, uncertainty or variation [8].

It is a two-step process time update and measurement update. It requires a state space model of the system. In first step the states of the system are estimated based only on the model and previous state. In second step the initial estimation is corrected based on the newly available measurement. Whenever the measurement is not available the measurement update step is skipped and time update is performed consecutively.

The process flow is depicted in Fig. 1[5].

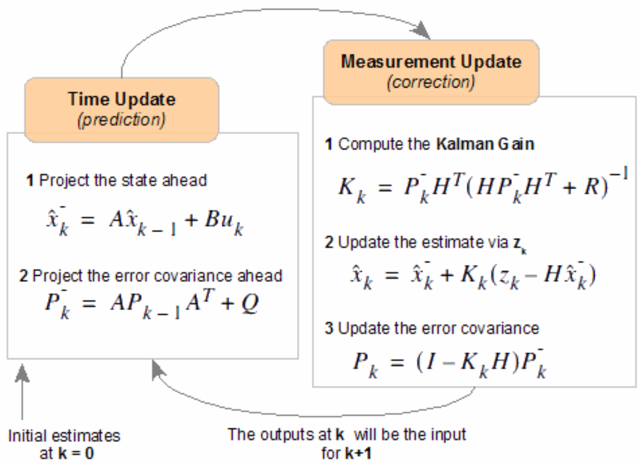


Fig. 1. Process flow of Kalman Estimation.

### B. Plant Model

The state space model of the plant is obtained from the physical equations with Distance Travelled and Energy consumed as states. The parameter values are given in TABLE II.

The corresponding matrices of SS model are as follows:

A= [1 0;0 1], B= [1 0 0;280 1.062 10526.31]
C= [1 0;0 1], D=0

The measurement of the distance is directly available. However, the energy measurement is not direct. It is obtained from the SOC measurement and total usable energy capacity of the battery in kwh (100%-20%).

Initially the processes noise covariance (Q) and measurement noise covariance (R) are assumed small. By changing the Q and R matrices the behavior of the Kalman estimator is observed.

KPIT Technologies provided the required data logs of electric bus and related vehicle information.

## III. ESTIMATION OF ENERGY CONSUMPTION

The estimation requires plant input-output data, Plant model and Kalman Filter. The input vector is

U= [u1 u2 u3]

U consists of speed (u1) and acceleration (a) terms.

Also, here u2=(u1) ^3 and u3=(u1*a)

The data logging frequency is 1 Hz.

### A. Abbreviations and Acronyms

BMS: Battery Management System

EV: Electric Vehicle

RDR: Remaining Driving Range

SOC: State of Charge

SS: State Space

### B. Units

TABLE I. Parameters and Units

| ***Parameter*** | ***Unit*** |
|---|---|
| Speed | m/s |
| Acceleration | m/s^2 |
| Voltage | V |
| Current | A |
| Distance | m |
| Battery Energy Capacity | kwh |
| Range | km |

TABLE II. Parameters and Values

| ***Parameter*** | ***Value*** |
|---|---|
| Vehicle weight | 10000 kg |
| Front surface area | 5.6 m^2 |
| Rolling coefficient | 0.003 |
| Drag coefficient | 0.3 |
| Gravitational acceleration | 9.8 m/s^2 |
| Battery Energy Capacity | 31104 kwh |
| Useful Battery Energy | 24883.2 kwh |
| Expected Range | ~120 km |
| Air Density | 1.2020 |
| Tire Radius | 0.3985 m |

| | |
|---|---|
| Transmission Efficiency | 95% |
| Gear Ratio | 13.65 |

### C. Equations

The tractive force is addition of the four different components as Inertial Force, Aerodynamic drag force, Rolling resistance and Grade force. The Fig. 2 shows all the forces acting on the moving vehicle.

The state space mode is created such that it incorporates all these forces.

The output of the SS model is discrete integral of velocity and power which gives distance covered and energy consumed.

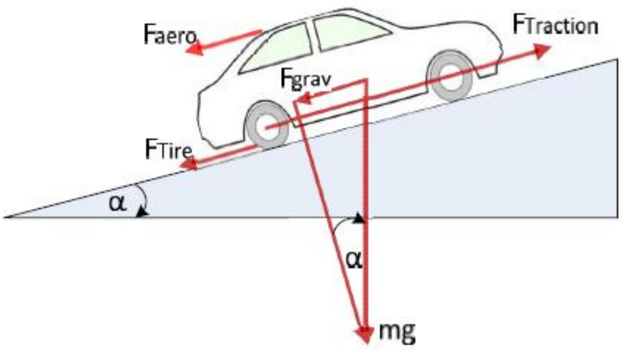


Fig. 2. Free body diagram of an electric vehicle along a slope.

$$F_{tractive} = F_{inertial} + F_{aero} + F_{tire} + F_{grav} \quad (1)$$

$$F_{inertial} = M \times a \quad (2)$$

$$F\_aero = \frac{1}{2} \times \rho \times C_d \times A \times v^2 \quad (3)$$

$$F_{tire} = C_{rr} \times M \times g \times \cos\alpha \quad (4)$$

$$F_{grav} = M \times g \times \sin\alpha \quad (5)$$

$$P = \frac{F_{tractive} \times v}{\eta_{trans}} \quad (6)$$

Here power is obtained directly from tractive force instead of torque calculation for simplicity as the torque calculations give same power output with transmission efficiency which is included in (6).

A Kalman filter is obtained for this plant model using control system toolbox of MATLAB [7] and both plant model and filter are simulated to observe the results.

The block diagram of Kalman filter estimation process is shown in Fig. 3.

Input and output of the plant are available from the logged data. Preprocessing is required to obtain the outputs in desired format such as energy consumption is obtained from SOC. Distance is initialized from 0 km.

Plant inputs are given to time update step of the Kalman filter to get initial estimation and it is corrected based on available measurement in second step.

The estimated energy consumption and distance travelled is used to calculate the range in next step.

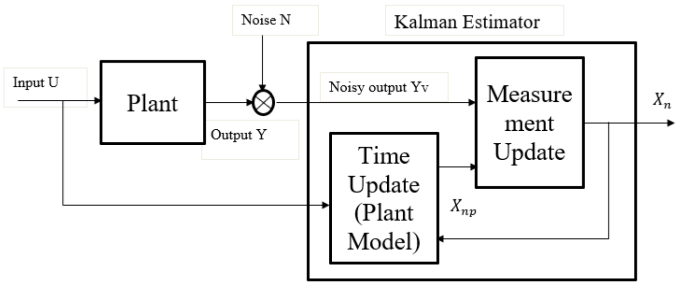


Fig. 3. Block diagram of Kalman Filter Estimation.

## IV. ESTIMATION OF REMAINING RANGE

### A. Fuel Efficiency Ratio

Fuel efficiency in case of electric vehicle is generally expressed as ration of number of watt-hour consumed per kilometer travelled (wh/km).

$$Fuel\ Efficiency = \frac{Energy\ Consumption}{Distance\ Covered} \quad (7)$$

As both the quantities of the ratio are available from the Kalman filter, Fuel efficiency is calculated corresponding to each measurement. This dynamic value of fuel efficiency improves the range calculation rather than using a static value.

It is suggested that taking average of dynamic fuel efficiency with static and standard fuel efficiency may improve the range estimation. In such case historic, static, dynamic, standard values of the efficiencies are averaged to get a normalized Fuel efficiency ratio [6].

### B. Remaining Battery Energy Capacity

It is expressed in watt-hour and obtained by subtracting the energy consumed from maximum useful energy capacity (wh). This value is also calculated corresponding to each measurement.

### C. Remaining Range

It is given by following ratio and expressed in kilometers.

$$Remaining\ Range = \frac{Remaining\ Battery\ Energy\ Capacity}{Fuel\ Efficiency} \quad (8)$$

This value is also calculated corresponding to each measurement. The estimated remaining range is shown in Fig. 6.

## V. RESULTS AND DISCUSSION

### A. Energy Consumption

The graph in figure shows the estimated energy consumption with measured energy consumption and plant model energy consumption.

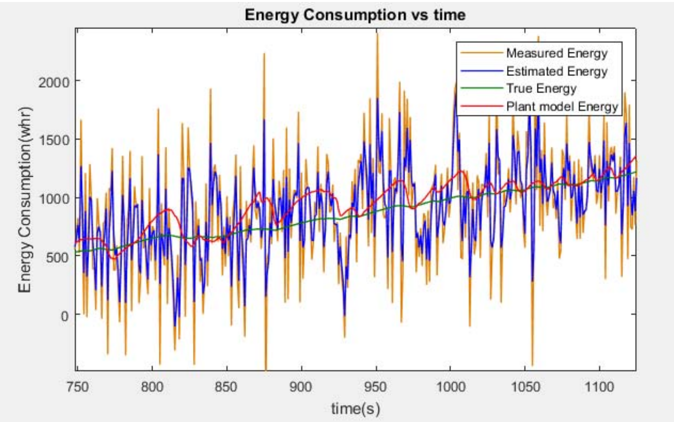


Fig. 4. Energy consumption with small measurement noise covariance.

In Fig. 4 the measurement noise covariance (R) is small hence the estimation closely follows the measurements. Consequently, error between true energy and estimated energy is large.

In Fig. 5 the R is increased 10000 folds then it is observed that estimation is closely follows the plant model output. Consequently, error between true energy and estimated energy is reduced as shown in Fig. 7.

Here the plant model is not accurate representation of the plant. There is a drift between plant output and plant model output. It is due to the dynamics which are missed out while building the plant model. However, Kalman filter try to minimize this drift.

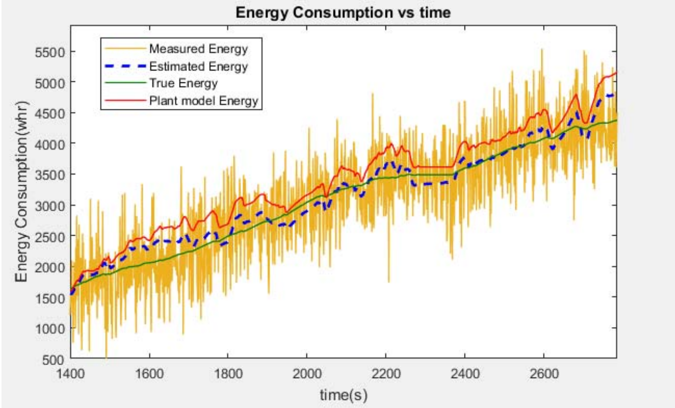


Fig. 5. Energy consumption with large measurement noise covariance.

### B. Range Estimation

The Fig. 6 shows the estimated range varying with the SOC. The spikes in the range at each integer SOC value is due to the fact that the step size of the BMS is 1% for SOC measurement. SOC changes in steps of 1%. The spikes can be reduced using small step size for SOC such as 100%-99.99%. Here a moving average filter is implemented to reduce the spikes.

It is observed that the filter does not estimate range accurately at initial stage. This is because initially the distance covered is very small which causes large variations is fuel efficiency ratio.

Ones sufficient distance is covered Kalman filter accurately estimates the remaining range. This issue can be resolved by using only historic and standard fuel efficiency ratio to calculate range at initial stage and then switching over to dynamic fuel efficiency later.

The full range of the electric bus under consideration is tested as 120-122 km through multiple full discharge drives (100% to 20%) while the Kalman filter estimates it to around 125 km after removing the spikes in the graph.

Also, it closely follows the variations in range as the vehicle travels.

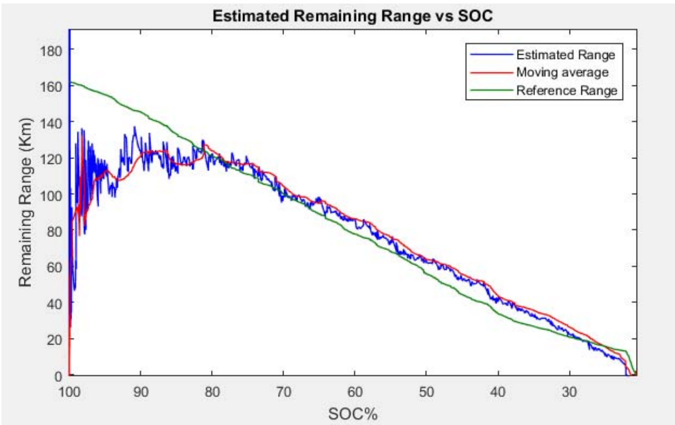


Fig. 6. Estimated remaining range with SOC.

In Fig. 7 error between true energy and measured energy is compared with the error between true and estimated energy. It is observed that the error is significantly reduced after the Kalman filtering process.

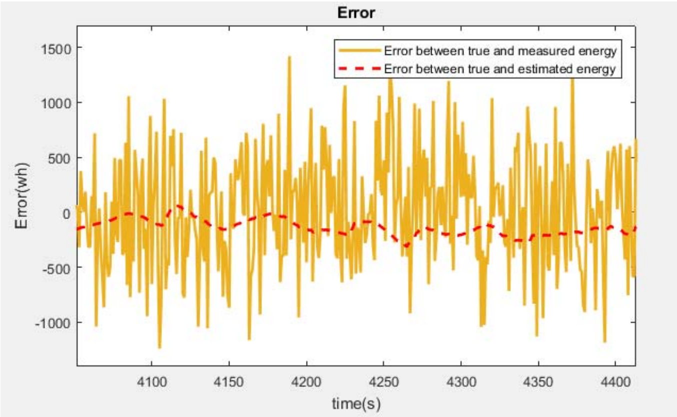


Fig. 7. Reduction in error after estimation.

## VI. CONCLUSION AND FUTURE WORK

In this paper, a model-based approach for estimating the remaining range is implemented. The estimator takes into account both disturbances in the plant model and noise in measurements while estimating energy consumption. It accurately estimates the remaining range except at initial stage. The initial error in the range estimation can be reduced using static or historic fuel efficiency value at start. The dynamic battery model can be used in future work to obtain the remaining battery energy capacity. The spikes in the Range estimation can be reduced using SOC values with small step size.

## ACKNOWLEDGMENT

The authors would like to thank KPIT Technologies, Pune for supporting the project.

## REFERENCES

[1] Javier A. Oliva, Christoph Weihrauch, Torsten Bertram, "Model-based remaining driving range prediction in electric vehicles by using particle filtering and Markov chains," 2013 World Electric Vehicle Symposium and Exhibition (EVS27), Year: 2013, Pages: 1 – 10.

[2] Javier A. Oliva, Christoph Weihrauch, Torsten Bertram, "A Model-Based Approach for Predicting the Remaining Driving Range in Electric Vehicles," Annual Conference of the Prognostics and Health Management Society 2013.

[3] Habiballah Rahimi-Eichi, Mo-Yuen Chow, "Big-data framework for electric vehicle range estimation," IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society, Year: 2014, Pages: 5628 – 5634.

[4] Anastasia Bolovinou, Ioannis Bakas, Angelos Amditis, Francesco Mastrandrea, Walter Vinciotti, "Online prediction of an electric vehicle remaining range based on regression analysis," 2014 IEEE International Electric Vehicle Conference (IEVC), Year: 2014, Pages: 1 - 8.

[5] http://bilgin.esme.org/BitsAndBytes/KalmanFilterforDummies

[6] US20130073113A1, "Vehicle and method for estimating a range for the vehicle."

[7] Mathworks documentation on Control System Toolbox.

[8] Video Lecture series on Kalman Filtering on www.ilectureonline.com