

An Approach of Applying Machine Learning for Range Prediction for LD, HD Commercial Electrical Trucks Energy Management

¹Balaji Srinivasan,

Research scholar,
Anna University
Chennai , India
sribalajitech@gmail.com

²J. Devi Shree,

Faculty of Electrical and Electronics Engineering,
Coimbatore Institute of Technology,
Coimbatore, India
devishreecit@gmail.com

Abstract—This paper investigates the range anxiety problem in the electric truck (light and heavy duty) commercial truck. Predicting range is popular in passenger car. The necessity of predicting range in passenger car is connected to customer delight and comfortability. Whereas necessity of predicting range in commercial vehicle is connected to Target Cost of Ownership (TCO) recovery especially for fleet business. TCO recovery is mainly connected to capital cost and running cost. Capital cost is based on vehicle overall cost in which battery cost is the predominant one. Running cost is based on the distance covered by charging in which mileage is the predominant factor. The range of the EV truck depend on road profile, battery (parameters like SOC, SOH), driver driving behavior, particularly this research is focused on commercial vehicle payload, tire pressure & rolling resistance. This paper has two step approach. First step is to realize the range estimation related to tire pressure and rolling resistance. The second step is correlating this range estimation with respect to payload of the vehicle. In passenger car payload is more or less fixed. However, in the commercial vehicles kind of load carrying medium duty or heavy-duty vehicle where load carrying is based on the trip and delivery schedule. The load on the vehicle influences the rolling resistance and mileage of the vehicle. In more, precise the paper describes the deeper thinking approach to estimate the range accurately by considering rolling resistance with respect to tire pressure and pay load in the truck while driving. This is in addition to the traditional data considerations like weather conditions, driving behavior, other power train and battery related information like (torque demand, Battery SOC, SOH and aging). In order to achieve effective range prediction method, it is proposed to use machine learning algorithm to estimate and find the remaining distance to reach (along with respect to payload). Indirectly the model would identify any deviation in the tire pressure, which increases the rolling resistance because of which the energy depletion will be faster than the expected or idle conditions. Online fleet data will be used as a training data to train the model. With matured model, predicting the range in advance can be done by feeding trip and delivery schedule. In addition, attempt is made to implement the scalable battery based on the trip delivery schedule. Hence, TCO recovery will be faster through optimum battery estimation before the actual trip take place.

Keywords—*Electric truck, Range prediction, energy depletion, machine learning*

1 INTRODUCTION

Latest research reveals that EV truck could increase for 15% of global truck sales by 2030. Three factors determine the attractiveness 1) ROI (return of investment) 2) charging infrastructure 3) National regulations.

The first influencing factor for the EV truck attractiveness is the ROI or cost parity of these EV trucks compared to Diesel alternatives. Since many vehicle, related parameters are invisible to determine the major factor for energy depletion, considerable capacity of the battery size will be available as buffer (safety margin or multiplication factor). The trade-off between sizes of the battery (Capacity), energy demand for daily average range to be as optimal as possible. Because the cost of the battery As a result, once EV truck have lower total cost of ownership (TCO)[3], many fleet owners are expected to switch their fleets in to BEV truck.

The second and third driving factors are electrical infrastructure readiness and national regulations, which are all not in the scope of this paper.

Most of the research towards range estimation concentrates on passenger car EV vehicle. In this paper, the focus is on EV light duty and heavy-duty vehicle in different applications (stop and go, delivery after long drive). The most cost-effective application seems to be in the light duty truck segment that drives a relatively average distance of 100 to 200 Kilometre per day, which has opportunity of stop and go in every delivery to the shops, mean time it can be charged. This segment is likely to reach cost break-even point with IC engine-based vehicle. For cases like parcel delivery and small retail delivery the vehicle, starts with full load of good and on the go part of the materials will be delivered. Therefore, there are chances that vehicle payload will be gradually decreased till the last delivery happens and hence pay load decreases. Hence, in LD vehicle (stop and go) has 2 major opportunity (1) to optimise the battery capacity (2) need to predict the range to go. The novelty highlighted in this research considers the payload decrease as how best it influence the energy demand (Acceleration demand) and reduce the power loss due to rolling resistance. The rolling resistance is connected to pay load, tire pressure and type of the tire in addition to other

vehicle level parameters like SOC, SOH, Vehicle speed, driving cycle and road conditions.

With this new approach suitable machine learning algorithms like regressive algorithm and rain forest algorithm have been chosen to train the model. This trained model will again get the real time data and able to predict the range to cover with the given delivery schedule. This algorithm also planned to indirectly detect the deflation of the tire pressure against the cold play card value and inform to the driver about the reason of depletion of the energy faster. Another by-product of the approach is to estimate the optimal battery size needed with respect to the preloaded trip- delivery schedule. Based on the result from the algorithm modular battery can be added or removed (Scalable or switchable battery). This will provide flexibility to choose the capacity of the battery based on the trip-delivery schedule in turn it gives optimal capital investment and running cost of the EV vehicle. This helps vehicle owners to achieve the TCO[3] faster than conventional methods.

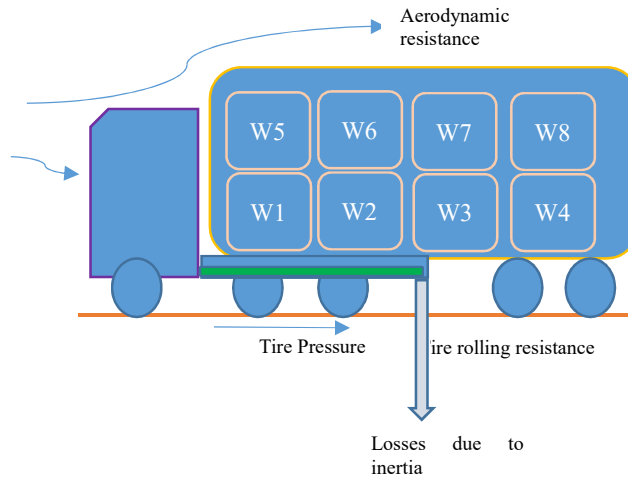


Fig 1 EV truck with full payload and energy loss model

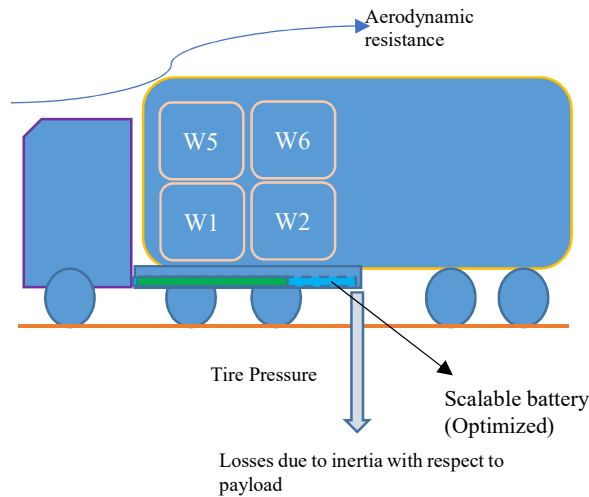


Fig 2 EV truck with partial payload and energy loss model

2 MATLAB Model

The energy management based on the loss model has been analysed in the multiple step approach. The first step with the help of MATLAB vehicle model. The MATLAB EV model consists of various subsystems like driver, brake, motor, driveline, battery and tire models. The model has been simulated with different driving cycles. The focus in this paper is with respect to UDDS driving cycle.

2.1 Driver Subsystem

The inputs to this subsystem is vehicle current speed and reference speed from the drive cycle. The drive cycle data is obtained from the workspace. The chosen drive cycle is UDDS. The vehicle speed is subtracted from the vehicle speed and sent to the PID controller to generate a driver command APP (Accelerator Pedal Position) and BPP (Brake Pedal Position). From PID controller it is sent to a saturation block to set the saturation limits for APP and BPP.

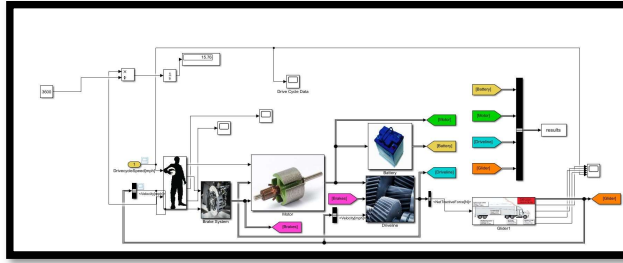


Fig 3 MATLAB vehicle model

2.2 Brake Subsystem

The inputs to this subsystem is BPP from Driver and vehicle speed. BPP is multiplied by a gain of 100. Its separated into two to obtain friction brake force and regenerative brake force. To generate friction brake force it is multiplied by gain. To generate regenerative brake force it is first multiplied with gain and after with (wheel radius / gear ratio) and this output is sent to a switch. In this regenerative brake torque is obtained. To obtain this vehicles speed is compared with a constant value of 5. If it is greater than 5 then its output is 1. The brake torque is applied.

2.3 Motor Subsystem

The inputs to this subsystem are APP, motor speed and regenerative braking command. Inside this subsystem there are other subsystems like motor torque limiter, regenerative torque limiter and motor loss. The motor torque limiter is used to calculate the maximum amount of torque which can be generated from the APP and motor speed input and also to calculate the allowable regenerative torque. In the regenerative torque limiter, the regenerative torque is generated based on the regenerative braking command. The motor loss is used to calculate the motor losses.

2.4 Vehicle Subsystem

This subsystem is used to generate the vehicle speed. The vehicle speed is obtained from the acceleration. The acceleration is given by equation 2

$$F_{AERO} = (0.5 * \rho * C_D * A_F * V^2) \quad (1)$$

$$a = (F_{TR} - F_{AERO} - F_{GRADE} - F_{RR}) / m_I \quad (2)$$

$$F_{GRADE} = m * g * \sin \Theta \quad (3)$$

$$F_{RR} = m * g * C_{RR} \quad (4)$$

Where

F_{TR} - is tractive force

F_{AERO} - is the aerodynamic force and it is given by equation (1)

ρ - is the air density

C_D - is the drag

A_F - is the frontal area of the vehicle

V - is the velocity of the vehicle

F_{GRADE} - is the grade force and it is given by equation (3)

m - is the mass of the vehicle

G - is the gravity

Θ - is the inclination angle of the vehicle

F_{RR} - is the rolling resistance force and it is given by equation (4)

C_{RR} - is the coefficient of rolling resistance

2.5 Role of tire in the EV Energy management

It should be noted that tire pressure is not constant during truck operation. When the truck carries full payload for long distance the temperature of the tire increases which in turn increases the pressure inside the tire. When the truck is running in the cold zone, the temperature will decrease which decreases the pressure inside the tire.

However, when there is an inadequate pressure in big vehicles like truck where the payload will be relatively high compared to passenger cars the impact will be high.

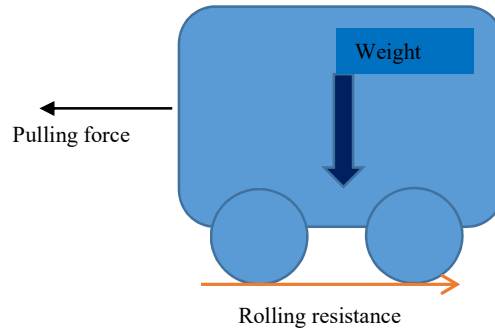


Fig 4 Tire pressure Vs Rolling resistance

Tire pressure and rolling resistance of the tire are connected each other. This contributes the energy depletion in the EV vehicle. Normally this will be assumed constant in the entire journey of the vehicle and when the value is relatively small it will be ignored.

In this research the rolling resistance of the tire with respect to pressure and payload is closely analysed and co-related with energy management of the battery electrical trucks.

2.6 Rolling resistance and range

In general, the forces operating to resist vehicle motion can be categorized in the following four areas— aerodynamic drag, rolling resistance, gradient resistance, and inertia. Since this paper is centered on tire technologies, the main area of focus in this section is rolling resistance. When tires roll on the road, mechanical energy is converted to heat. The tire consumes a portion of the power transmitted to wheels, leaving less energy for the vehicle to propagate. There are two forms of energy losses from tire: i) hysteresis loss, and ii) deformation loss. The viscoelasticity of the tire material gives rise to the hysteresis losses. Roughly, 90 percent of the total loss of energy through tires is related to the hysteresis losses. Deformation of the wheels, the deformation of the roadbed surface, and movement below the surface are the main factors that contribute to the rolling resistance. Additionally, wheel diameter, speed, load on wheel, surface adhesion, sliding, and relative micro-sliding between the surfaces of contact also contributes towards the rolling resistance. The losses due to hysteresis depends strongly on the material properties of the wheel or tire and the surface. However, over the life of a tire, the rolling resistance reduces as the tread wears down and hence the fuel efficiency of the vehicle actually improves slightly (assuming that tire inflation remains constant).

The rolling resistance force acting on a tire is a product of rolling resistance coefficient and the weight on the tire. The rolling resistance force acting on the tire increases as the payload increases. At an equilibrium temperature, slower running speeds reduce rolling resistance. The stronger influence of thermal factors diminishes the hysteresis losses and increases tire pressure rather than the dynamic factors, which cause its increase. Starting from the observation that in most situations, the rolling resistance is almost proportional to the vertical load, researchers have defined the ratio of these values as the rolling resistance coefficient. Actually, when measuring at equilibrium temperature, this coefficient is almost constant or slightly decreasing for radial truck tires.

2.7 Range Deterioration Calculation

Generally, in a vehicle all the energy which is given as input is not available at the output some of them are generally lost in the conversion process and rest in overcoming various forces like inertia, internal friction, aerodynamic forces and rolling resistance. In an ICE vehicle range deterioration is not a big issue since it refueling time is less but in case of EV it has a big impact on the consumer choice over EV. Inertia forces which depends on vehicle mass and speed. Gravitational forces depend on the slope and mass. Aerodynamic forces depend on the wind, the speed of the movement and the vehicle's shape. Rolling resistance is due to the visco-elastic properties of the tire. As tire gets older it gets deformed due to the load. Due to this deformation there is an energy loss which is called as rolling resistance. Tire pressure also has an impact on rolling resistance. It gets increased due to decrease in tire pressure. The relation between the coefficient of rolling resistance, velocity and tire pressure is given by

$$CRR = 0.005 + (1/p) * (0.01 + 0.0095(V/100)^2) \quad (5)$$

Where,

CRR – is the coefficient of rolling resistance

p – is the tire pressure (in bar)

V – is the vehicle velocity (in m/s).

So, a considerable amount of energy is being wasted in overcoming these forces and with the use of in wheel motors the change in tire pressure can be predicted and informed so that the rider can avoid unwanted range depletion. The prediction

is done by measuring the change in the current profile of the in-wheel motor. Since the motor is directly connected to the wheel any changes in the tire pressure will induce a change in the motor's current profile which will be sensed and an intimation will be sent to the rider.

From equation (5) the coefficient of rolling resistance is calculated for various tire pressure at a velocity of 100 m/s. For various tire pressure the respective rolling resistance is substituted and the model is simulated. As the tire pressure gets reduced there is a reduction in the distance covered by the vehicle. The data is shown in the Table 1. The graph between tire pressure, range and range depletion is plotted and shown in the Fig 5 and Fig 6. The other direct evident to show the effect of tire pressure in the range depletion is current demanded by the electric motor in the EV vehicle. In the fig 7 shows the simulation result of motor current distribution with respect to various tire pressure. It shows due to decay in tire pressure increases the rolling resistance intern current consumption also relatively increases. Therefore, it will deplete the battery SOC faster than the idle pressure as shown in the fig 6. Similarly, payload also impacts the depletion rate, Fig 8 & 9 show the rate of depletion to reach 50% of SOC with respect to two different payloads 14000Kg and 1400Kg. it is evident that payload reduction in the stop and delivery vehicle can yield the battery SOC.

Table 1 Distance covered and Range Depletion with different tire pressure

Tire Pressure (Psi)	Distance (Km)	Range Depletion (Km)
32	36.2056	-
30	35.6379	0.5
28	35.1774	1.0
24	33.9213	2.28
22	33.0495	3.15
20	32.3522	3.85
18	31.6324	4.57
16	30.2242	5.98

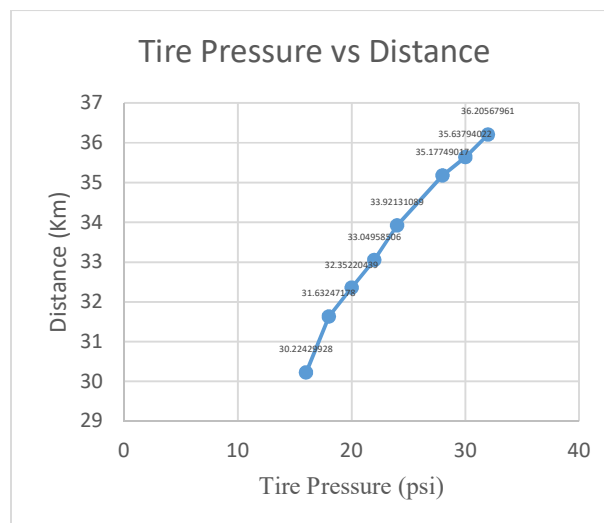


Fig 5 Tire Pressure vs Distance

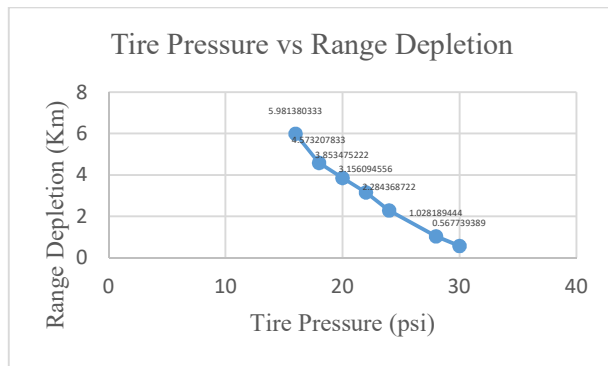


Fig 6 Tire Pressure Vs Range Depletion

2.8. Current Profile Analysis

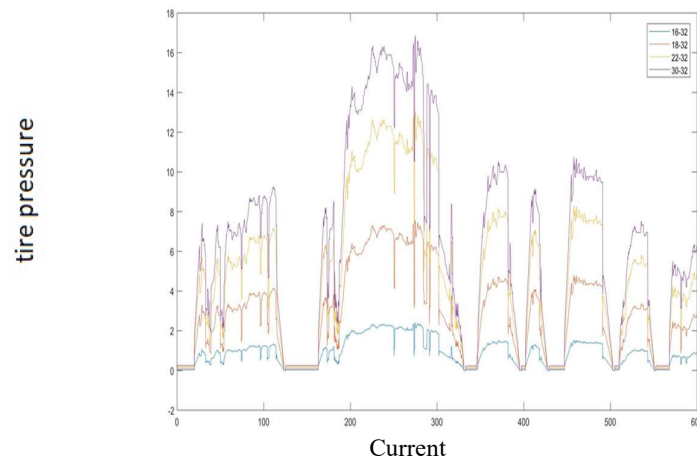


Fig 7 Variations in current with respect to various tire pressure (32 psi as an idle pressure)

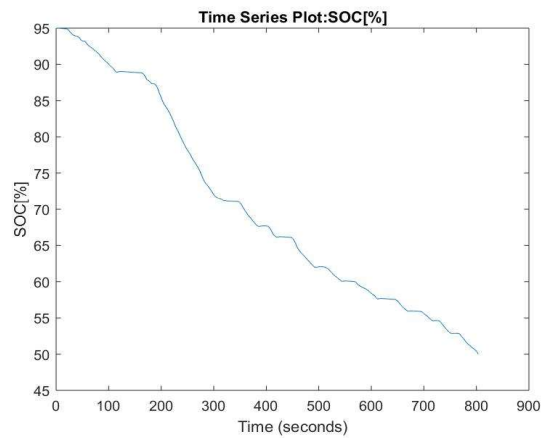


Fig 8 SOC with 14000 kg mass (time taken to reach 50% SOC)

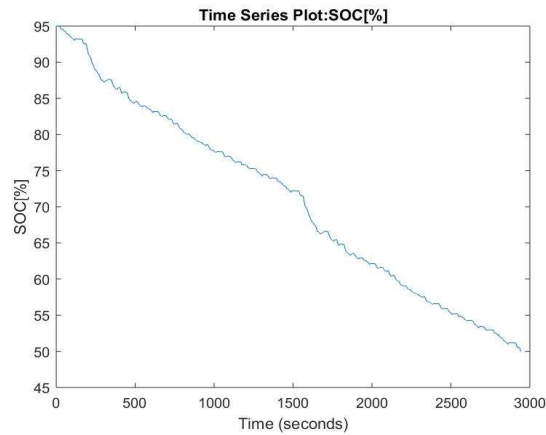


Fig 9 SOC with 2300 kg mass (time taken to reach 50% SOC)

3 Machine learning for Electric truck – Commercial vehicle

3.1 Machine Learning

Machine learning is the science of getting system to become more accurate in predicting outcomes without being explicitly programmed. The basic premise of machine learning is to build system that can receive input data (learning phase) and use statistical analysis to predict an output (Predictable phase).

3.2 ML models for prediction of the Dynamic Range of EV

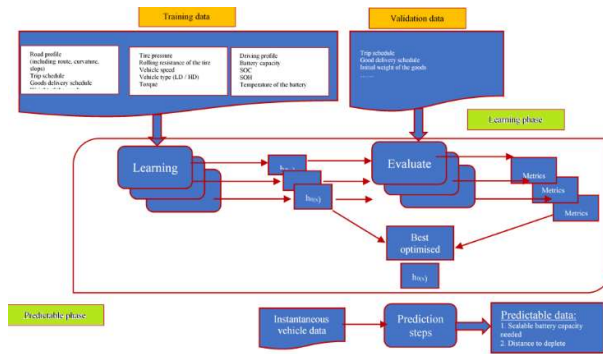


Fig 10 Machine Learning model for Range prediction

Proposed to use two different ML algorithms to the problem of finding the dynamic range. They are multiple variable Non-Linear regression and Random Forest [1]

3.2.1 Multiple Variable Non-Linear regression

Multiple variable (linear / nonlinear) regression explains the relationship between one dependent variable (the predicted variable) which in our problem is the dynamic range and many independent variables (the predictor variables) which for our application are, speed, state of charge of the battery, tire pressure, truck load, temperature and route profile. Multiple variable Non-linear regression can be thought as a particular type of regression analysis in which the observed data are modeled by a nonlinear combination of the model parameters and depends on more than one input variable. The equation for the nonlinear regression function is

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \dots + \beta_r X_i^r + u_i \quad (6)$$

Y_i - is the predicted output

β_0, β_1 are the parameters that need to optimize $X_1, X_2, X_3, \dots, X_n$ are the features, which are given as input to the algorithm.

3.2.2 Regression analysis with Non-Linear functions

The values for theta are provided and minimizing the above equation using Gradient Descent first and then arrive at the optimum values of the parameters theta. The equation are solved using Normal Equation method to verify the veracity of our previous results.

The simple linear regression model is first applied to the mapping function and to remove the bias in the estimates of the range, penalizing larger values of the powers of theta through appropriately choosing the regularization parameter lambda. This will help to smooth the variations as the curve flattens at the end.

3.2.3 Linear Regression with Multiple variables with Regularization

Regression analysis explains the relationship between one dependent variable (the predicted variable) which in our problem is the dynamic range and many independent variables (the predictor variables) which for our application are, speed, state of charge of the battery, tyre pressure, truck load, temperature and route profile. The cost function for multiple variables with the regularization parameter lambda.

Linear regression can be implemented as

- A cost function that helps us fit the best possible line to our data
- To choose the values of theta which are the parameters
- To choose the parameters so that the squared error between predicted output and the actual output or the squared error cost function is at its minimum
- To find the average of the sum over the entire dataset

So the goal is to find the optimum values of theta and lambda so that the cost function $J(\theta)$ is minimized

$$J(\theta) = \frac{1}{2m} \left[\sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2 + \lambda \sum_{j=1}^n \theta_j^2 \right]$$
$$\min_{\theta} J(\theta) \quad (7)$$

The equation to be minimized is the cost function $J(\theta)$

- 1 to m – ‘m’ is the number of training examples or training samples
- 1 to n – ‘n’ is the number of features that are present in the input
- $J(\theta)$ is the cost function that needs to be minimized
- λ is the regularization parameter
- $H(\theta)$ is the predicted output of range value
- y superscript ‘i’ is the actual output
- $X_1, x_2, x_3, \dots, X_n$ are the features such as temperature, tyre pressure, truck load, current ground speed, state of charge of the battery and route profile
- $\theta_1, \theta_2, \theta_3, \dots, \theta_n, \dots$ are the parameters whose values has to be find and set to the optimum value. The values of the parameters θ_1, θ_2 are the values that need to found in order to minimize the cost function.

3.3 Random forests

Random forests [1] is a special kind of ensemble learning method used in machine learning to do both classification and regression. It consists of creating multiple sets of random data using bootstrapping from the given dataset. Then at each step of the way while creating decision trees, a different set of input features are chosen to build the tree. So, there are two types of randomness introduced here. One is the randomness introduced due the random nature of the bootstrapped data given as input to the decision trees. The other randomness is created by randomly choosing different features at every step while creating each decision trees.

Since multiple trees at random are created, it is called as random forest. Building multiple decision trees reduces the variance error considerably and, in some situations, can also reduce the error due to bias.

Random forests are also used in machine learning for regression. At least 0 to 100 trees are built and each tree predicts the continuously varying value and the final answer will be the average of all the values outputted by each decision tree. When doing classification, a majority of the votes of all the classes outputted by each decision tree are taken. In summary while doing regression average is taken and majority vote while doing classification.

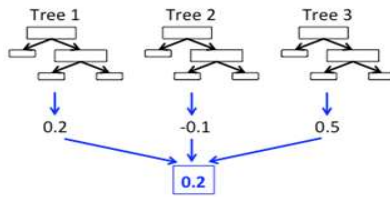


Fig 11 Example for regression (Ensemble Model)

So, regression is done through ensemble learning by taking average

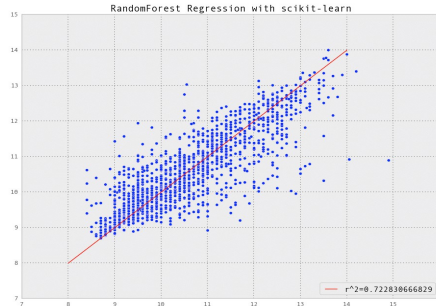
$$\text{Regression: } \hat{f}_{\text{rf}}^B(x) = \frac{1}{B} \sum_{b=1}^B T_b(x) \quad (8)$$

- B is the total number of trees
- T_b is a specific tree that you want to build,
- where 'b' is the bth tree you are building,
- $f(x)$ is the mapping function

By using ensemble learning, the variance of the output is reduced which is shown by the following relation. If B is increased which is the number of trees built the variance reduces. If Sigma or Ro is reduced then also the variance comes down.

$$\text{Var} \left(\frac{1}{B} \sum_{i=1}^B T_i(c) \right) \Rightarrow \rho\sigma^2 + \sigma^2 \frac{1-\rho}{B} \quad (9) \quad (10)$$

- Sigma is variance in data,
- $\rho * \sigma$ is co-variance of data;
- B is the number of trees you build.



Successful testing of regression using models generated with random forests[8]

- Among other choices for range estimation, Random forest algorithm is chosen, as it offers considerable advantages in problems such as dynamic range prediction. Some of the reasons for our choice of random forest algorithm are,
 - Random forest can handle completely different features, that is like "Apples and Oranges" features
 - Random forests show a considerable Robustness to outliers
 - Works well both for binary class and multiclass problems
 - Works with a "small" learning set, even if the available dataset is small random forests tend to produce reasonably accurate results
 - Scalability (large learning set)
 - Prediction accuracy – Random forests are the most accurate learning algorithm for this kind of range detection problems
 - Parameter tuning

Random forest is also a better choice, since the optimum choice of features that give the best results in building individual trees can be found . While building each tree, at every node a different set of features has been chosen . This helps us to understand which are the feature having the most impact.

4 Scalable battery on demand with respect to trip-delivery schedule

Fleet owner will feed the data via system Based on the trip – delivery schedule. The machine learning algoirthm based on the vehicle model it will calculate the range to complete deplete as well predict the required battery to be fixed (with standard buffer) and informed to the owner before start of the trip it self

5 Future scope of work

There is a lot of scope for future work, More detailed non-linear functions such as Neural Network based methods can be used. When the number of features increase, GHSOM (Growing Hierarchical Self Organizing Map), deep learning based neural networks can be experimented to do regression. In due course it is also likely that an ensemble technique such as bagging or stacking multiple machine learning models could yield better results that are consistent over a large range. The results of random forests can be simulated in MATLAB and other mathematical modeling tools to arrive at the appropriate method for range estimation.

6 Conclusion

Three different types of machine learning models are used here and arrived at the one that provide best results in terms of scalability of the data, accuracy, appropriate features in the problem domain that yield better error reduction. Simple linear regression with multiple variables with regularization parameter lambda has been used, then polynomial regression (with multiple variables) with non-linear function and then using the ensemble learning technique random forests. Here a set of features has been chosen at each node in tree building randomize the choice of features. Gradient Descent and Normal equation methods are used to solve in order to minimize the cost function. All the results show a decreasing trend for range as the tyre pressure decreases, as temperature increases.

References

- [1] 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, ISBN 978-1-4799-4032-5.
- [2] Chung-Hong Lee, (Member, IEEE), and Chih-Hung Wu, (Member, IEEE), “ A Novel Big Data Modeling Method for Improving Driving Range Estimation of EVs”, [IEEE Access](#), Vol. 3, pp: 1980 – 1993, October 2015.
- [3] Cathy Macharis, Philippe Lebeau, Joeri Van Mierlo, and Kenneth Lebeau , “Electric versus conventional vehicles for logistics: A total cost of ownership” , EVS27 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium, Barcelona, Spain, November 17-20, 2013.
- [4] Chew KW and Yong YR, “ Effectiveness Comparison of Range Estimator for Battery Electric Vehicles”, Advances in Automobile Engineering, Vol 5(1), 2016.
- [5] J. Cao, N. Schoeld, and A. Emadi, ``Battery balancing methods: A comprehensive review," in Proc. IEEE Vehicle Power Propuls. Conf. (VPPC), Sep. 2008, pp. 16.
- [6] <https://towardsdatascience.com/machine-learning-with-python-easy-and-robust-method-to-fit-nonlinear-data-19e8a1ddb49>
- [7] <https://databricks.com/blog/2015/01/21/random-forests-and-boosting-in-ml-lib.html>
- [8] <http://blog.yhat.com/posts/comparing-random-forests-in-python-and-r.html>