Journal of Electronics and Informatics (ISSN: 2582-3825)
www.irojournals.com/iroei/

Electric Bike Range Estimation using Fuzzy Logic Controller

G. S. Naganathan[1], S. Selvaperumal[2], R. Nagarajan[3], P. Nedumal Pugazhenthi[4]

Department of Electrical and Electronics Engineering, Syed Ammal Engineering College, Tamil Nadu, India

E-mail: [1]naganathangs@gmail.com, [2]perumal.om@gmail.com, [3]nagarajnsr@gmail.com, [4]neduaupci@gmail.com

Abstract

Electric Vehicles (EV) are the prompt solution to significantly lowering the use of fossil fuels and CO2 emissions from the transport industry. There is a continuing growth in the number of EVs in use, but their huge acceptance by customers is associated to the quality they can provide. Nowadays, different types of electric vehicles are moving toward green awareness, and one among them is the electric motorcycle which is a considerable vehicle in India. Though there are many benefits of driving electric motorcycles, because of the limited driving range and inadequate charging stations, it is still not generally accepted in the industry. Range anxiety is the major market concern that is solved by the implementation of an additional range estimating technique that can ease the "range anxiety" caused by the restricted range of EVs. Therefore, this paper proposes a fuzzy logic controller model for the estimation of the EV range based on the battery's state of charge and the load's power usage. In this work, the load power consumption of the vehicle and the status of the battery charge are selected as inputs and the EV range is selected as a Fuzzy Logic Controller output. This model is implemented in the Matlab/Simulink environment.

Keywords: Fuzzy Logic Controller (FLC), Electric Vehicle (EV), Electric Bike, State of Charge (SOC)

1. Introduction

Electric Vehicles (EVs) are now growing in popularity due to several benefits, such as low levels of harmful emissions, high performance, low noise rates and numerous available energy resources [1]. EVs contain essential technologies which are capable of helping to avoid the energy crisis and contamination of the environment [2,3]. Compared with

DOI: https://doi.org/10.36548/jei.2022.4.002
Received: 01.10.2022, received in revised form: 04.11.2022, accepted: 20.11.2022, published: 30.11.2022

traditional fossil fuel vehicles, the EV is extremely energy efficient [4]. It is possible to identify EVs in two ways. They are Battery Electric Vehicles (BEV) and Hybrid Electric Vehicles (HEV). HEVs commonly have an Internal Combustion (IC) engine and moderately sized energy storage system. BEVs convert chemical energy into stored electric energy in rechargeable battery packs. BEVs are better than IC engine vehicles because transportation costs and air pollution can be reduced by such vehicles [5].

Due to the lack of charging facilities, long charging times and the range of EVs [6,7], the number of EVs used is not greater than that of conventional vehicles. Range anxiety is the biggest issue of the customer. Therefore, understanding how far they can go with their current battery power is very critical for EV users. It's not easy to forecast the EV driving range because, the driving range evaluation depends upon several factors, such as driving style, vehicle total weight, longitudinal forces exchanged between the tires and the road, the inclination of the road runway and the aerodynamic forces caused by the movement. In EVs, how far the vehicle can go on its present energy supply is closely linked to the quantity of battery charge available and the actual consumption of power [8-10]. The calculation of the driving range of EVs relies on multiple methods. In order to minimize the computing effort, it can be clasified into two types, namely precise estimation and rough estimation [11,12]. For accurate assessment, the vehicle model determines a least energy track between the present location and the destination through road links to inform the vehicle driver. For rough estimation, driving habits, full and remaining battery energy and vehicle with airconditioner are considered to estimate the remaining driving distance.

A Fuzzy Logic Controller (FLC) technique was employed to calculate the driving distance of EV in [13]. In [14], a model was established for estimating the driving range through the analysis of the operational mechanism according to driving conditions and energy usage of the EV. In [15], a data-based modeling was suggested to enhance the precision of the BEV driving distance calculation. The operation data of BEV was collected from a cloud system and cycle-life test. The ranked self-organizing map was applied to examine the energy usage and then, the BEV driving distance was calculated. Paper [16] adopted the radial basis function neural network for BEV remnant range estimation in Beijing. The most important aspect of the study was that, the range for the vehicle is carried out with FLC. A system was proposed that can produce fast solutions by avoiding complex mathematical modeling and calculations.

Among the EVs, electric bikes receive great attention from the Indian people due to its wide application potential. FLC can produce fast solutions by avoiding complex mathematical modeling and calculations. Therefore, the electric bike modeling with its range estimate using Fuzzy Logic Controller has been proposed in this article. In this study, assuming that certain parameters have direct impact on the electric bike drive mechanism such as the environmental conditions, the road type and the external forces influencing the bike, it is believed that modifications in these parameters and battery charging status can be determined based on the vehicle's instant power usage. Hence, Status of battery Charge (SOC) and instant power usage of electric bike are used as input and the range of the electric bike is used as a output of the FLC. A MATLAB/ Simulink environment is developed for modeling the electric bike and its range estimating is performed using FLC.

2. Materials and Methods

2.1 Modeling of Electric Bike

The design of an electric bike begins from the physical relations, which is based on the Newton’s second law of motion, by considering forces that act on the motion of the vehicle, such as wind force, gravity force, force of rolling resistance, and force of inertia. Forces acting on the vehicle motion is shown in the Fig.1. The physical resistance of all components influencing a vehicle's movement dynamics has to be calculated in order to assure the movement of the vehicle [17 - 20].

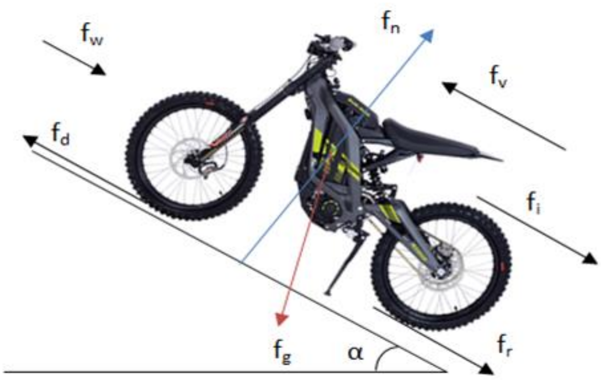

Figure 1. Forces acting on the bike

Vehicle inertia force $f_i = m_v * m_a$ (1)

Vehicle weight force $f_r = m_v g \cos(a)$ Newton (2)

Rolling resistance force $f_r = f_n C_{st}$ Newton (3)

$$C_t = \left(1 + \frac{3.6}{100} * f_v\right) * 0.01 \quad (4)$$

Gravity force $f_g = m_v g\, sin(a)$ Newton (5)

Wind force $f_w = \left(\frac{1}{2}\rho_{air} * C_d * A_{ya}(f_v + V_w)^2\right)$ (6)

Driving force of the vehicle $f_t = (f_i + f_g + f_r + f_w)$ Newton (7)

Where,

f_t is the vehicle driving force (N),

f_i is the force of vehicle inertia (N),

f_r is the force of rolling resistance (N),

f_g is the gravity force of the vehicle (N),

f_W is the wind resistance force (N),

f_n is the normal weight force of the vehicle (N),

m_V is the vehicle mass (kg),

f_V is the vehicle speed (m/s),

a is the road slope (degrees),

m_a is the acceleration of the vehicle (m/s^2),

A_{ya} is the surface area of the vehicle (m^2),

g is the acceleration force of gravity (m/s^2),

ρ_{air} is the air density (kg/m^3),

C_d is the aerodynamic coefficient,

f_w is the speed of the wind(m/s) and

C_{st} is the rolling resistance coefficient,

Some parameters of these change dynamically and some of the parameters are fixed [14]. The vehicle driving power can be calculated with Eq. (8).

$$P_f = (f_t * f_v) \text{ Watts} \quad (8)$$

From Eq. (9), the torque generated in mechanical systems can be determined.

$$T_m = (f_t * R_w) \text{ Nm} \quad (9)$$

The wheel torque is determined using Eq. (10).

$$T_w = \frac{T_m}{2} \text{ Nm} \quad (10)$$

From Eq. (11), the wheel angular speed can be calculated.

$$N_{\omega} = \frac{f_v}{R_w} \quad \text{Rad/Sec} \tag{11}$$

where, R_w is the radius of the wheel (m).

Using the above equations, the required power can be determined for the movement of the EV and the drive system of electric bike can be developed. The technical parameters of the electric bike model are set up based on the parameters of the Hero Electric Flash Li model. Table 1 lists the technical specifications and parameters of the electric bike employed in the MATLAB simulation.

Table 1. Technical parameters of the electric bike

Parameter	Symbol	Value
Total vehicle mass	M_V	155 Kg
Speed of vehicle	F_V	25 Km/h
Rear wheel radius	R_w	0.3149 m
Rolling resistance coefficient	C_{st}	0.025
Gravitational acceleration	G	9.8 m/s^2
Air density	ρ_{air}	1.22 kg/m^3
Wind speed	F_W	0 m/s
Drag area	$A_{ya} * f_v$	0.4 m^2
Battery nominal voltage	-	48 Volt
Battery rated capacity	-	28 Ah
Motor power	-	250 Watts
Range	-	65 Km/charge

2.2 State of battery charge

One of the most significant factor for batterry is the battery's State of Charge (SOC). The cell is assumed to be entirely discharged if the SOC is 0%, while a 100% SOC means that the cell is completely charged. The SOC estimation methods are categorized according to various methodologies in the various literatures. However, there are four main categories such as book-keeping estimation, direct measurement, hybrid methods, and adaptive systems focused by some literatures [21, 22]. Most SOC calculations depend partly or entirely on direct measurement because of the simple measurement of the terminal voltage of the battery. In this work, the battery SOC is calculated based on direct measurement using Eq.(12).

$$SOC = (v^2 * 9.7769) - (v * 164) + 603 \tag{12}$$

Where, v is the battery voltage (V) and SOC is in %.

2.3 Fuzzy Logic Controller Design

FLC is a method to resolve problems that are too complex to be interpreted quantitatively. It is based on fuzzy set theory, proposed by Prof. Zadeh [23]. Fig.2 depicts the fundamental FLC model used in this work. It is made up of three parts, namely fuzzification, defuzzification and Fuzzy Inference System (FIS). In this model, SOC of the battery and instantaneous power consumption of bike are selected as the input and the range of bike as the output. Mamdani type FLC is used to estimate the range. Fuzzification is the mechanism of translating crisp input values of SOC and power into membership grades for linguistic terms of fuzzy sets. FIS is responsible for generating results from the knowledge-based rules of if-then linguistic statements. The fuzzy output value (bike range) is defuzzified into the crisp value by the defuzzification strategy.

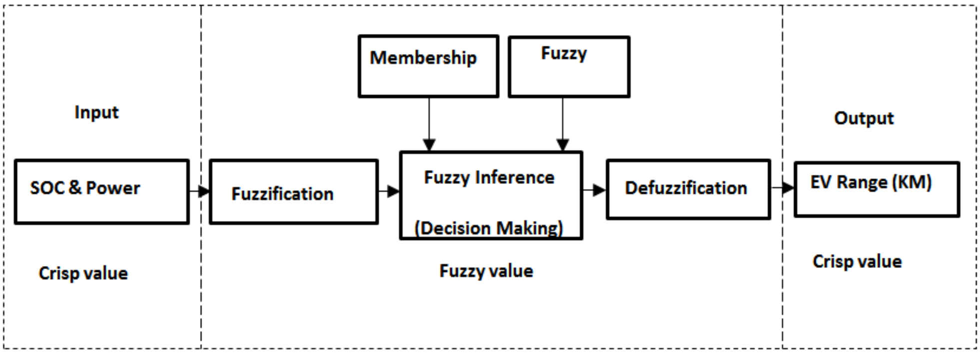

Figure 2. Conceptual FLC model

The membership functions of FLC input and output variables are shown in Fig.3, Fig.4 and Fig.5 and the corresponding linguistic variables are labeled as VL (Very Low), L (Low), N (Normal), H (High) and VH (Very High). For simplicity, triangular membership functions are considered for SOC which range according to Eqs. 1, 2 and 3. Based on the number of inputs and their linguistic variables, the number of rules relies. Two inputs (SOC, Power) with seven linguistic variables, each generating forty-nine fuzzy inference rules are listed in Table 2. Two rules are explained below for the illustration purpose. If SOC is 'VH' and power is 'VL', then the estimated range is 'VH'. If SOC is 'VL' and power is 'VH', then the estimated range is 'VL'. One sample output of FIS is shown in Fig.6. It shows that if the battery's SOC% is 40 and instantaneous power consumption of bike is 628.9 watts, then the estimated range of bike is 22.4 km.

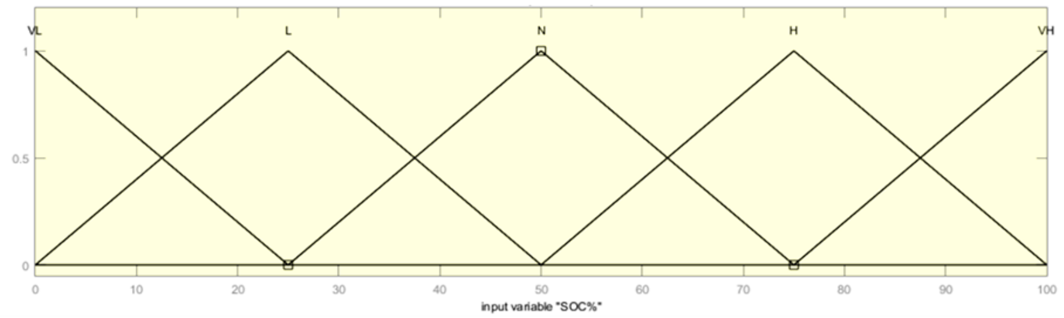

Figure 3. Membership functions of SOC%

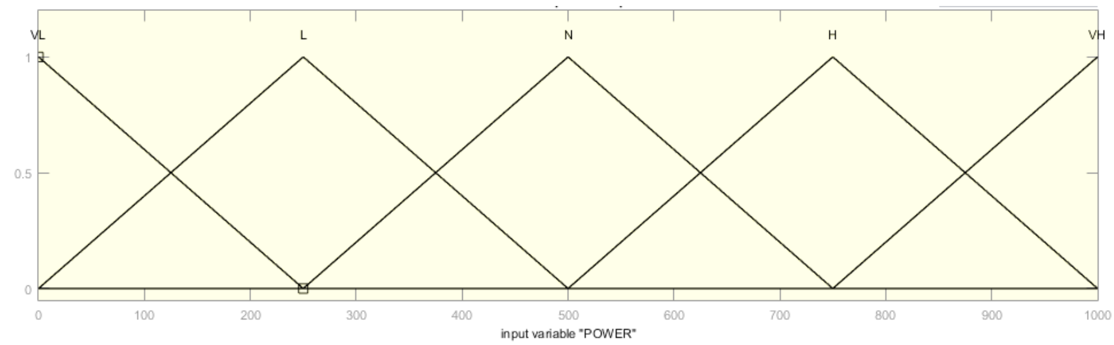

Figure 4. Membership functions of instantaneous power

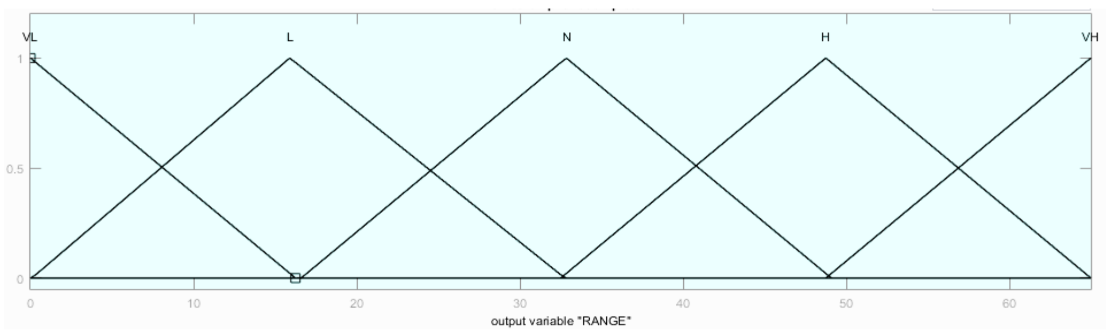

Figure 5. Membership functions of electric bike range

Table 2. Fuzzy inference rules

Power	SOC				
	VL	**L**	**N**	**H**	**VH**
VL	VL	N	H	VH	VH
L	VL	L	H	H	VH
N	VL	L	N	H	VH
H	VL	VL	L	N	H
VH	VL	VL	L	N	N

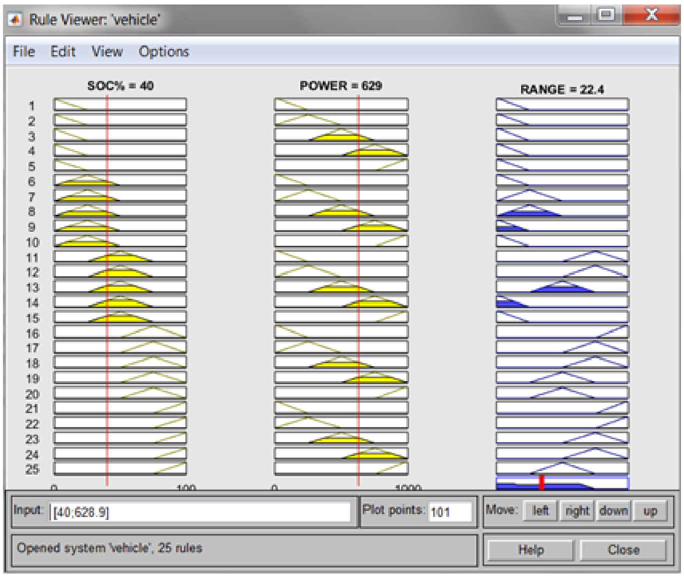

Figure 6. FIS sample output

2.4 Simulation Model

The entire simulink model of an electric bike is illustrated in Fig.7. It comprises of the electric bike body, battery, BLDC motor, converter, driving system and monitoring system. All the systems are implemented based on the equations used for modeling the bike, parameters and specifications of the electric bike as described earlier in the bike modeling section.

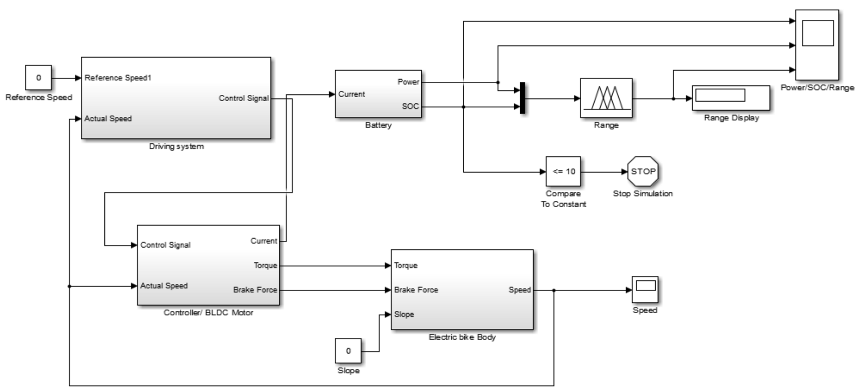

Figure 7. MATLAB Simulink model for Electric Bike

3. Results and Discussion

The positive slope of the path was only taken into account in this analysis because the battery can be charged by the regenerative braking of the bike as it goes downhill and the bike consumes less battery power and runs slowly as well. The driving distance coverage of the bike depends primarily on the battery's SOC and the battery's SOC depends on the bike's

ISSN: 2582-3825

power consumption. The bike's instantaneous power usage mainly depends on the load of the bike and road's slope.

Table 3. The performance results of FLC for bike without rider

Road Slope (%)	Battery SOC%	Instantaneous Power Consumption (Watts)	Range (Km)
0	40%	318.12	39.2
1		338.28	37.4
2		350.71	35.6
3		361.43	32.5
0	65%	318.12	49.2
1		338.28	46.9
2		350.71	43.2
3		361.43	41.1
0	90%	318.12	56.3
1		338.28	54.7
2		350.71	52.9
3		361.43	51.2

Table 4. The performance results of FLC for bike with a rider

Road Slope (%)	Battery SOC%	Instantaneous Power Consumption (Watts)	Range (Km)
0	40%	428.12	31.7
1		456.23	29.4
2		482.34	27.4
3		542.87	25.3
0	65%	428.12	45.5
1		456.23	42.8
2		482.34	41.9
3		542.87	41.8
0	90%	428.12	52.1
1		456.23	51.8
2		482.34	50.6
3		542.87	49.7

Table 5. The performance results of FLC for bike with two riders

Road Slope (%)	Battery SOC%	Instantaneous Power Consumption (Watts)	Range (Km)
0		628.92	22.4
1		676.13	19.7
2	40%	697.39	18.1
3		722.67	14.5
0		628.92	33.3
1	65%	676.13	31.1
2		697.39	29.7
3		722.67	27.8
0		628.92	41.5
1	90%	676.13	40.2
2		697.39	38.9
3		722.67	37.8

At first, the bike without the rider was taken into account in this work. The bike's weight was 155kg. Subsequently, the bike with a rider was taken into account. The load on the bike was 75kg and the bike's overall weight was 230kg. Next, attention was given to a bike with two riders. The weight of each person was considered to be 75kg, so the load on the vehicle was 150kg and the vehicle's overall weight was 305kg. The performance results of FLC under different road slopes and different levels of battery's SOC for bike without rider, with a rider and with two riders are shown in Table 3, Table 4 and Table 5 respectively. The results of Table 3 and Table 4 shows that the electric bike's instantaneous power consumption has increased as the slope of the road has increased and the range of the electric bike coverage has decreased.

4. Conclusion

In this work, a Fuzzy Logic Controller based electric bike range estimation system has been developed according to the dynamic vehicle parameters to notify the driver how far the vehicle can go. Instantaneous power consumption of the electric bike and SOC% of the battery are selected as inputs and the electric bike range is selected as an FLC output. Electric bike with a rider and electric bike with two riders are examined for range estimaton. It is evident that the modifications to the SOC parameters and the instantaneous power consumed by the bike, have a direct impact on the system output. Moreover, the road's slope has also affected the range estimation.

References

[1] Z. Guirong, Z. Henghai, L. Houyu, The driving control of pure electric vehicle, Proc. Environ. Sci, 2011, pp 433–438.

[2] Sarrafan K, Muttaqi KM, Sutanto D, Town GE, A real-time range indicator for EV susing web-based environmental data and sensorless estimation of regenerative braking power. IEEE Trans Veh Technol, 2018.

[3] Pan C, Dai W, Chen L,Wang L, Driving range estimation for electric vehicles based on driving condition identification and forecast, AIPAdv 2017.

[4] C. Gribben, Debunking the myth of EVs and smokestacks, Electro Automotive ,1996.

[5] M. NC Onat, O.T. Kucukvar, Conventional, hybrid, plug-in hybrid or electric vehicles? State-based comparative carbon and energy footprint analysis in the United States. Appl. Energy,2015, pp 36–49.

[6] S. Heath, P. Sant, B. Allen, Do you feel lucky? Why current range estimation methods are holding back EV adoption, 2013.

[7] J.G. Hayes, R.P.R. de Oliveira, S. Vaughan, M.G. Egan, Simplified electric vehicle power train models and range estimation, in: Vehicle Power and Propulsion Confere (VPPC), 2011 IEEE, 2011, pp 1–5.

[8] Franke T, Rauh N, Krems JF, Individual differences in BEV drivers' range stress during first encounter of a critical range situation. Appl Ergo, 2016, pp 28–35.

[9] Bi J, Wang Y, Sai Q, Ding C, Estimating remaining driving range of battery electric vehicles based on real-world data: a case study of Beijing, China, Energy, 2019, pp 833–43.

[10] Masjosthusmann C, Kohler U, Decius N, Buker U, A vehicle energy management system for a battery electric vehicle. 2012 IEEE Veh Power Propuls Conf (VPPC 2012), 2012, pp 339–344.

[11] Y. Zhang, W. Wang, Y. Kobayashi, K. Shirai, Remaining driving range estimation of electric vehicle, in: Electric Vehicle Conference (IEVC), 2012 IEEE International, IEEE, 2012, pp 1–7.

[12] E. Kim, J. Lee, K.G. Shin, Real-time prediction of battery power requirements for electric vehicles, in: Proceedings of the ACM/IEEE 4th International Conference on Cyber-Physical Systems, ACM, 2013, pp 11–20

[13] I. Cunningham, K. Burnham, Online use of the fuzzy transform in the estimation of electric vehicle range. Meas. Control, 2013, pp 277–282.

[14] W. X, J. Shen, Y. Li, K.Y. Lee, Data-driven modeling and predictive control for boiler–turbine unit. IEEE Trans. Energy. Convers, 2013, pp 470–481.

[15] Erdelic T, Caric T, A survey on the electric vehicle routing problem: variants and solution approaches. J Adv Transp 2019, 2019, pp 1–48.

[16] De Nunzio G, Thibault L, Energy-optimal driving range prediction for electric vehicles, IEEE Intell Veh Symp Proc 2017, pp 1608–1613.

[17] Hong J, Park S, Chang N, Accurate remaining range estimation for electric vehicles. Proc Asia South Pacific Des Autom Conf ASP-DAC 2016, pp 781–786.

[18] Qi, Chen Y, Li J, Control of electric vehicle, 2012.

[19] N. Watrin, B. Blunier, and A. Miraoui, Review of adaptive systems for lithium batteries state-of-charge and state-of-health estimation, in Proceedings of IEEE Transportation Electrification Conference and Expo,2012, pp. 1–6,

[20] V. Prajapati, H. Hess, E. J. William, A literature review of state of-charge estimation techniques applicable to lithium poly-carbon monoflouride (LI/CFx) battery, in Proceedings of the India International Conference on Power Electronics (IICPE '10), 2011, pp 1–8.

[21] N. Watrin, B. Blunier, A. Miraoui, Review of adaptive systems for lithium batteries state-of-charge and state-of-health estimation, in Proceedings of IEEE Transportation Electrification Conference and Expo, 2012, pp 1-6.

[22] V. Prajapati, H. Hess, E. J. William et al., A literature review of state of-charge estimation techniques applicable to lithium poly-carbon monoflouride (LI/CFx) battery, in Proceedings of the India International Conference on Power Electronics (IICPE '10), 2011, pp. 1–8.

[23] L.A.Zadeh, Fuzzy sets, Inform Control,1965, pp 338.