Annals of Electrical and Electronic Engineering, 2(5) 2019, Pages: 14-18

Published by IASE

Annals of Electrical and Electronic Engineering

Journal homepage: www.aeeej.org

Charge management of plug-in electric vehicles for distribution transformer life enhancement

J. R. da Silva *, P. M. de Oliveira, T. R. Lima, A. Z. de Freitas

Electronic and Electrical Engineering Department, Nove de Julho University, São Paulo, SP, Brazil

ARTICLE INFO

Article history:
Received 25 December 2018
Received in revised form
18 March 2019
Accepted 22 March 2019

Keywords:
Transformer
Hot spot
ANFIS
PEV

ABSTRACT

A large population of power transformers along with other power system grid infrastructures have been in service for decades and considered to be in their final ageing stage. On the other hand, due to economy and business growth in our era, the electricity demand is growing rapidly. Therefore, transformers became the most critical devices in power system due to their long repair or replacement time. Plug-in electric vehicles (PEV) have been identified as an option that can reduce criteria pollutant and greenhouse gas emissions associated with the transportation sector. The electricity demand of one of these vehicles is comparable to that of a typical U.S. household and thus clustering of PEVs in a neighborhood might have adverse effects on the transformer and disruption of service. In this paper, the electricity demand of a neighborhood is modeled based on measured vehicle and household data. Then the threshold temperature is determined to program the charging process. In the proposed method, we used adaptive neuro-fuzzy inference system (ANFIS). Simulation results show that the ANFIS can accurately predict the spot hot of transformer.

1. Introduction

Growing volatility in petroleum prices, security concerns, and anthropogenic climate change is contributing to increased interest towards alternative vehicle technologies (Yilmaz, 2015; Lausenhammer et al., 2016). Moreover, with the proliferation of distributed renewable energy sources and the structure of the future utility grid, the smart-grid, and incorporation of bidirectional digital communication, the mass integration of the Electric Vehicles (EVs) and PEVs into the automobile market today seem both economically, environmentally beneficial, and technologically feasible (Rathore and Roy, 2016; Esmaili and Goldoust, 2015; Hajforoosh et al., 2015).

Today, PEVs offer numerous advantages over conventional fuel based vehicles (Brooker and Qin, 2015), and given the potential large scale deployment of PEVs it is important that policy makers and electricity industry members understand the impact these vehicles will have on national electricity infrastructures (Dimitrova and Maréchal, 2015; Zhang and Xiong, 2015).

With increasing number of PEV connected to power systems for charging, there is a concern that existing distribution networks may become more heavily loaded than anticipated when they were designed. Low level of penetrations may result in little impact but, as the numbers increase, there could be a real possibility of local distribution networks being overwhelmed. Various studies have been carried out to evaluate whether the existing electricity network and generation capacity could accept the widespread adoption of PEVs (Clement-Nyns et al., 2009).

In Gong et al. (2012), a transformer thermal model was used to estimate the hot-spot temperature given the knowledge of load ratio and ambient temperature. Main inputs to the model, including residential load, ambient conditions, and vehicle parameters were taken from real data. The transformer insulation aging is mainly affected by the hot-spot temperature.

In Rutherford and Yousefzadeh (2011), the impact of the mass insertion and electricity consumption of the EVs and PHEVs on distribution transformers is analyzed. Various simulations of Lithium-Ion batteries and transformer loss of life are developed. The simulation results from realistic load and real ambient temperature data show that power management of the EV battery charge profile can help manage the loss of life of the distribution transformer. Two potential approaches for charge scheduling of the EV batteries are described and investigated, and show that intelligent coordination between charging stations has promise for mitigating unnecessary loss-of-life due to EV charging.

The aim of Geiles and Islam (2013) was to investigate the impact PEV charging imposes on local distribution transformer life in the presence of rooftop PV. The principal concept attained from this work is that PV generation coupled with PEV charging can delay and reduce the temperature rise of large oil immersed transformers. Furthermore, investigation finds that increased penetration of PEVs may have significant effect on distribution transformer loading. Therefore, utility companies must develop procedures or algorithms to identify these overload-susceptible transformers before they result in a high number of customer outages.

In Razeghi et al. (2014), the electricity demand of a Southern California neighborhood comprised of ten households is modeled using a statistical Monte Carlo method based on measured electricity demand and power factors. Each household is then assumed to house a PEV. The electricity required to fully charge the vehicle's battery is modeled based on real data of home arrival and departure times and driving patterns during a weekday, and vehicle type. The distribution transformer load serving this neighborhood is calculated, and a transformer thermal model is developed to track the hot spot temperature of the transformer for different cases and charging scenarios.

* *Corresponding Author.*
Email Address: j.r.daSilva@yahoo.com (J. R. da Silva)
https://doi.org/10.21833/AEEE.2019.05.003

Qian et al. (2015) presented a detailed methodology to quantify the increase in power transformers' loss of life as a result of the charging loads introduced to distribution systems by FEVs. Detailed mathematical models which take into account the stochastic nature of FEVs charging are developed and applied into the detailed transformer thermal model, which takes into consideration of all the major factors that determine transformer loss of life. Four FEV charging scenarios, named uncontrolled domestic charging, off-peak domestic charging, smart charging and uncontrolled public charging were simulated under various FEV penetration levels to investigate the effect of FEV charging load on the additional life consumption of power transformers.

This paper is organized as follow. Section two describes the ANFIS. Section three investigates the PEV impacts on transformers. Section four presents some simulation results and finally section five concludes the paper.

2. ANFIS

The ANFIS represents a useful neural network approach for the solution of function approximation problems. Data driven procedures for the synthesis of ANFIS networks are typically based on clustering a training set of numerical samples of the unknown function to be approximated. Since introduction, ANFIS networks have been successfully applied to classification tasks, rule-based process controls, pattern recognition problems and the like. Here a fuzzy inference system comprises of the fuzzy model proposed by Takagi, Sugeno and Kang (Chiu, 1994) to formalize a systematic approach to generate fuzzy rules from an input output data set.

For simplicity, it is assumed that the fuzzy inference system under consideration has two inputs and one output. The rule base contains two fuzzy if-then rules of Takagi and Sugeno (1983) type-2 as follows:

If x is A and y is B then z is f(x, y)

Where A and B are the fuzzy sets in the antecedents and $z = f(x, y)$ is a crisp function in the consequent. $f(x, y)$ is usually a polynomial for the input variables x and y. But it can also be any other function that can approximately describe the output of the system within the fuzzy region as specified by the antecedent. When $f(x, y)$ is a constant, a zero order Sugeno fuzzy model is formed, which may be considered to be a special case of Mamdani fuzzy inference system where each rule consequent is specified by a fuzzy singleton. If $f(x, y)$ is taken to be a first order polynomial a first order Takagi and Sugeno (1983) fuzzy model is formed. For a first order two-rule Takagi and Sugeno (1983) fuzzy inference system, the two rules may be stated as:

Rule1: If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$
Rule2: If x is A_2 and y is B_2 then $f_1 = p_2x + q_2y + r_2$

Here type-3 fuzzy inference system proposed by Takagi and Sugeno is used (Buragohain and Mahanta, 2008). In this inference system the output of each rule is a linear combination of input variables added by a constant term. The final output is the weighted average of each rule's output. The corresponding equivalent ANFIS structure is shown in Fig. 1.

The individual layers of this ANFIS structure are described below:

Layer 1: Every node i in this layer is adaptive with a node function

$$O_i^1 = \mu_{A_i}(x) \tag{2}$$

where x is the input to node i, A_i the linguistic variable associated with this node function and μ_{A_i} is the membership function of A_i. Usually $\mu_{A_i}(x)$ is chosen as

$$\mu_{A_i}(x) = \frac{1}{1+[(^{x-c_i}/_{a_i})^2]^{b_i}} \tag{3}$$

or

$$\mu_{A_i}(x) = \exp\left\{-(\frac{x-c_i}{a_i})^2\right\} \tag{4}$$

where x is the input and $\{a_i, b_i, c_i\}$ is the premise parameter set.

Layer 2: Each node in this layer is a fixed node which calculates the firing strength w_i of a rule. The output of each node is the product of all the incoming signals to it and is given by

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x), \mathrm{i} = 1,2 \tag{5}$$

Layer 3: Every node in this layer is a fixed node. Each ith node calculates the ratio of the ith rule's firing strength to the sum of firing strengths of all the rules. The output from the ith node is the normalized firing strength given by

$$O_i^3 = \overline{w} = \frac{w_i}{w_1+w_2}, \mathrm{i} = 1,2 \tag{6}$$

Layer 4: Every node in this layer is an adaptive node with a node function given by

$$O_i^4 = \overline{w_i}f_i = \overline{w_i}(p_ix + q_iy + r_i) \tag{7}$$

where $\overline{w_i}$ is the output of Layer 3 and $\{p_i, q_i, r_i\}$ is the consequent parameter set.

Layer 5: This layer comprises of only one fixed node that calculates the overall output as the summation of all incoming signals, i.e.:

$$O_i^5 = overall\mathrm{output} = \sum_i \overline{w_i}f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

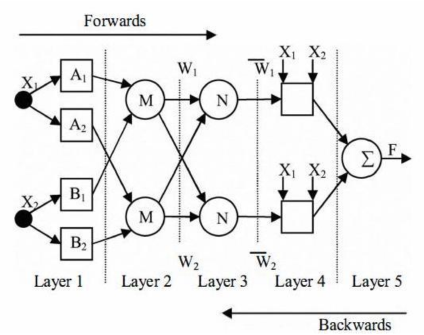

Fig. 1. ANFIS structure.

3. Impact of PEV charges on transformers

For the transformer thermal model, load ratio and ambient temperature are the two inputs, and the hot-spot and top oil temperatures can be obtained correspondingly. For our case study, one year ambient temperature data of 2009 is available, and one year of base load ratio data is also available. For the load ratio that would be added by PEV charging, in this section we assume an even charging case. For the even charging case, we assume the charging rate for PEV is adjustable from 0 to maximum value of the charging rate, and the PEVs are charged from 7 pm to 6 am the next day with a constant charging rate. This case in practice would be difficult to realize without the use of a smart meter or other necessary technologies. However, this charge case was simulated to see the transformer thermal model response, and to see a nearly optimal charging as a bench mark. The specifications of test system are listed in Tables 1-3.

One case of charging load comparison of the base load and the load with 6 PEVs (for 6 houses which share the same transformer) with even charging is shown in Fig. 2. The time for this case is in summer, so the ambient temperature would be relatively high. The base load in night is lower than day time. The corresponding temperatures of top-oil and hot-spot are in Fig. 3. The response of top-oil temperature is much slower than hot-spot temperature since the time constant of oil is much longer than winding. The hot-spot temperature was increased considerably due to the charging load from the 6 PEVs.

Similarly, to see how different penetrations of PEV would affect the transformer hot-spot temperature, simulation of 2–6 PEVs were carried out and compared together with the base load case. From the results presented in Fig. 4, higher penetration of PEVs would cause much higher hot-spot temperature.

Table 1
Test system specifications.

Transformer capacity (KVA)	Peak load (KW)	No. consumers	Consumer type	No. Transformer
800	762.5	210	Residential	1-2-3-5
800	745	240	Residential	4-6-7-8
630	574	195	Residential	9-10-11-12-13
1250	1110	1	Industry	22-23-24-25-26
800	740	15	Commercial	14-15-16-17-18
630	616.7	1	Official	19-20- 21

Table 2
Temperature information.

Peak load (Winter)	Temperature (Winter)	Peak load (Summer)	Temperature (Summer)	Hour
67	1	64	30	0-1
63	0.5	60	29.5	1-2
60	0.5	58	29.2	2-3
59	0	56	29	3-4
59	-0.7	56	28.7	4-5
60	0	58	28.5	5-6
74	0.9	64	28.2	6-7
86	3.3	76	29.8	7-8
85	5.5	87	31.8	8-9
96	7	95	33.9	9-10
96	8.7	99	35.9	10-11
95	10.5	100	37.1	11-12
95	11	99	38.4	12-13
95	10.5	100	39.6	13-14
93	9.5	100	40	14-15
94	9	97	40	15-16
99	8	96	39.6	16-17
100	7.2	96	38.2	17-18
100	7	93	36.8	18-19
96	6	92	35.4	19-20
91	5.5	92	33.9	20-21
83	5.5	93	32.5	21-22
73	4.5	87	31.7	22-23
63	2	72	30.8	23-24

Table 3
PEV specifications.

	Battery capacity	Efficiency (Electric)	Efficiency (gas)
Unit	(kWh)	(kWh/km)	(litre/km)
Minimum	8	0.35	0.05
Maximum	23	0.45	0.15

4. Simulation results

In this paper an intelligent technique based on fuzzy rules is proposed to PEV charge programming. As mentioned, hot spot temperature has high effect on transformer life loss. Table 4 presents the relation between transformer hot spot temperature and transformer life loss. It can be seen that in 98 degree, there is no life loss. But with increasing in temperature, the life loss rate increased rapidly. Therefore in this study we used ANFIS to predict the hot spot by using load and ambient temperature as effective input.

The ANFIS is used to predict the hot spot temperature. Based on the predicted hot spot temperature, the central controller makes decision to permit new car charging or no. In this study we used 140 centigrade degree as threshold temperature. The ANFIS accuracy has vital role in the control system. Table 5 represents ANFIS performance of different value of radii. It can be seen that there is no linear relation between radii and ANFIS performance. Therefore the value of radii must be selected by trial and error. The variation of ANFIS accuracy versus radii is plotted in Fig. 5.

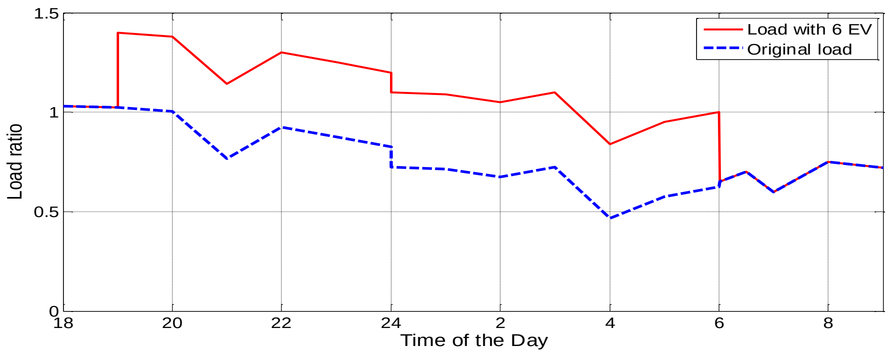

Fig. 2. Compare of base load to condition with 6 PEV even charging.

Table 4
Relation between transformer hot spot temperature and transformer life loss.

hot spot	140	134	128	122	116	110	104	98	92	86	80
life loss rate	128	64	32	16	8	4	2	1	0.5	0.25	0.125

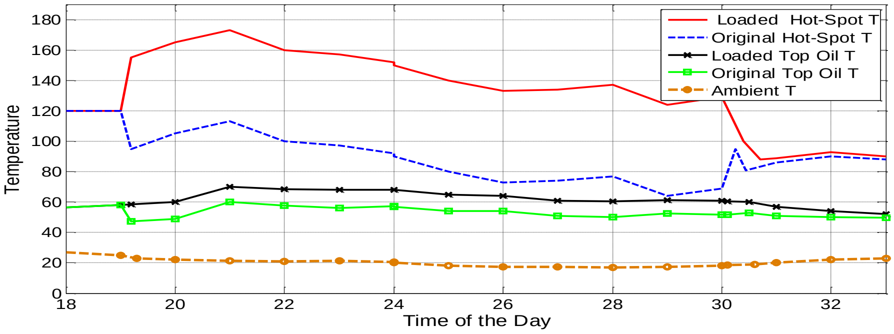

Fig. 3. Compare of temperature responses of base load to condition with PEV even charging.

a

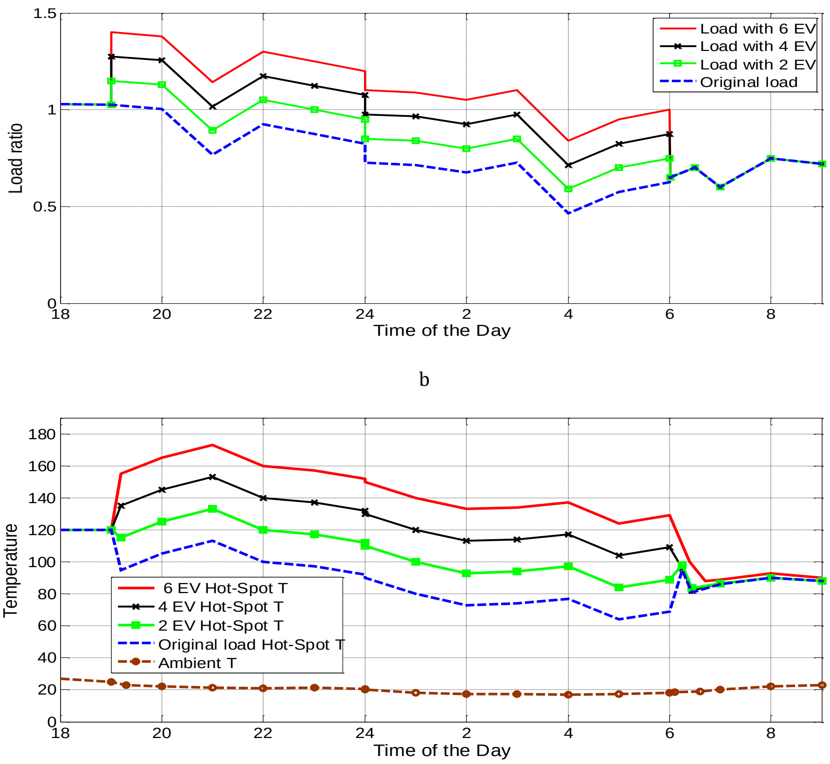

Fig. 4. Comparison of (a) load and (b) temperature responses with different penetration of PEV.

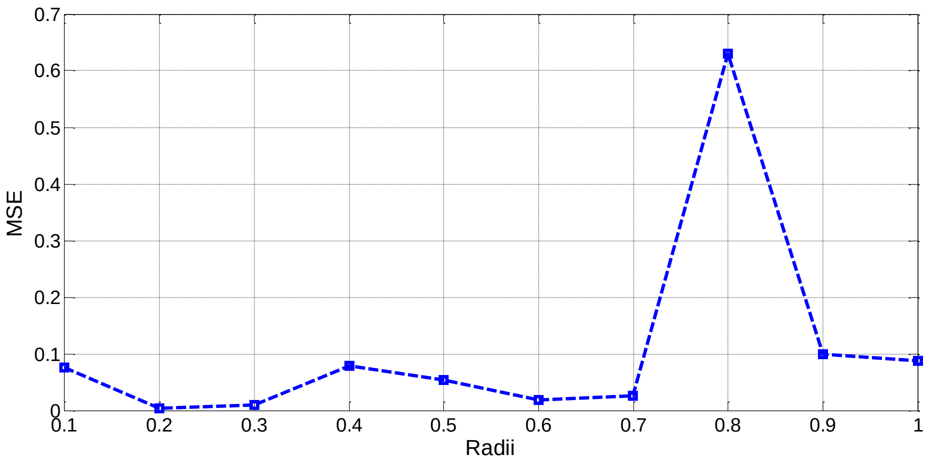

Fig. 5. Radii effect on ANFIS performance.

5. Conclusion

The effect of uncontrolled electric vehicle charging on the distribution side is considerable and has the potential to affect the life of distribution components. This especially has significant impact on secondary-distribution transformers in residential zones. With smart grid implementation, assessment for reliability of feeder-level components becomes more crucial. In this paper we introduced and investigated the ANFIS application to optimal programming of PEV charging. In the proposed method we used ANFIS to predict the hot spot temperature. Simulation results show that the ANFIS can accurately predict the hot spot.

Table 5
ANFIS performance.

Radii	MSE
0.1	0.076
0.2	0.0031
0.3	0.0095
0.4	0.079
0.5	0.054
0.6	0.019
0.7	0.026
0.8	0.63
0.9	0.099
1	0.088

References

Brooker RP and Qin N (2015). Identification of potential locations of electric vehicle supply equipment. Journal of Power Sources, 299: 76-84. https://doi.org/10.1016/j.jpowsour.2015.08.097

Buragohain M and Mahanta C (2008). A novel approach for ANFIS modelling based on full factorial design. Applied Soft Computing, 8(1): 609-625. https://doi.org/10.1016/j.asoc.2007.03.010

Chiu SL (1994). Fuzzy model identification based on cluster estimation. Journal of Intelligent and Fuzzy Systems, 2(3): 267-278. https://doi.org/10.3233/IFS-1994-2306

Clement-Nyns K, Haesen E, and Driesen J (2009). The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. IEEE Transactions on Power Systems, 25(1): 371-380. https://doi.org/10.1109/TPWRS.2009.2036481

Dimitrova Z and Maréchal F (2015). Techno-economic design of hybrid electric vehicles using multi objective optimization techniques. Energy, 91: 630-644. https://doi.org/10.1016/j.energy.2015.08.073

Esmaili M and Goldoust A (2015). Multi-objective optimal charging of plug-in electric vehicles in unbalanced distribution networks. International Journal of Electrical Power and Energy Systems, 73: 644-652. https://doi.org/10.1016/j.ijepes.2015.06.001

Geiles TJ and Islam S (2013). Impact of PEV charging and rooftop PV penetration on distribution transformer life. In the IEEE Power and Energy Society General Meeting, IEEE, Vancouver, Canada: 1-5. https://doi.org/10.1109/PESMG.2013.6672211

Gong Q, Midlam-Mohler S, Marano V, and Rizzoni G (2012). Study of PEV charging on residential distribution transformer life. IEEE Transactions on Smart Grid, 3(1): 404-412. https://doi.org/10.1109/TSG.2011.2163650

Hajforoosh S, Masoum MA, and Islam SM (2015). Real-time charging coordination of plug-in electric vehicles based on hybrid fuzzy discrete particle swarm optimization. Electric Power Systems Research, 128: 19-29. https://doi.org/10.1016/j.epsr.2015.06.019

Lausenhammer W, Engel D, and Green R (2016). Utilizing capabilities of plug in electric vehicles with a new demand response optimization software framework: Okeanos. International Journal of Electrical Power and Energy Systems, 75: 1-7. https://doi.org/10.1016/j.ijepes.2015.08.014

Qian K, Zhou C, and Yuan Y (2015). Impacts of high penetration level of fully electric vehicles charging loads on the thermal ageing of power transformers. International Journal of Electrical Power and Energy Systems, 65: 102-112. https://doi.org/10.1016/j.ijepes.2014.09.040

Rathore C and Roy R (2016). Impact of wind uncertainty, plug-in-electric vehicles and demand response program on transmission network expansion planning. International Journal of Electrical Power and Energy Systems, 75: 59-73. https://doi.org/10.1016/j.ijepes.2015.07.040

Razeghi G, Zhang L, Brown T, and Samuelsen S (2014). Impacts of plug-in hybrid electric vehicles on a residential transformer using stochastic and empirical analysis. Journal of Power Sources, 252: 277-285. https://doi.org/10.1016/j.jpowsour.2013.11.089

Rutherford MJ and Yousefzadeh V (2011). The impact of electric vehicle battery charging on distribution transformers. In the Twenty-Sixth Annual IEEE Applied Power Electronics Conference and Exposition, IEEE, Fort Worth, USA: 396-400. https://doi.org/10.1109/APEC.2011.5744627

Takagi T and Sugeno M (1983). Derivation of fuzzy control rule from human operator's control actions. IFAC Proceedings Volumes, 16(13): 55-60. https://doi.org/10.1016/S1474-6670(17)62005-6

Yilmaz M (2015). Limitations/capabilities of electric machine technologies and modeling approaches for electric motor design and analysis in plug-in electric vehicle applications. Renewable and Sustainable Energy Reviews, 52: 80-99. https://doi.org/10.1016/j.rser.2015.07.033

Zhang S and Xiong R (2015). Adaptive energy management of a plug-in hybrid electric vehicle based on driving pattern recognition and dynamic programming. Applied Energy, 155: 68-78. https://doi.org/10.1016/j.apenergy.2015.06.003