Finding the Range of PHEV Controller Parameters Using the Confidence Interval (CI) Estimation from Prediction Model

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ABSTRACT

The major problem of wind energy sources always occurs in an isolated small power system is a serious frequency deviation problem which is a result of the intermittent nature of wind power. An alternative way to relive this frequency deviation is applying a plug-in hybrid electric vehicle (PHEV) to control power in the system. However, improper setting PHEV power deviation controller cannot manage the real power unbalance deviation in the isolated small power system and cause worse frequency control to follow. In order to avoid unsuitable setting PHEV power charging control a machine learning method, an artificial neural network (ANN) was used to find suitable values set of PHEV controller parameters. In selection, the PHEV controller parameters using confidence interval (CI) from the suitable values set for optimizing the PHEV controller parameters. The results show the superior frequency control effects of the proposed PI controllers.

Keywords: Artificial neural network, Confidence interval, Parameter Optimization, Isolated small power system, Plug-in hybrid electric vehicle

INTRODUCTION

The wind energy source was gained popularity recently especially for isolated small power system like a small island because of low set up cost and efficiency in power generation (Nikolaidis et al. 2016; Miyauchi et al. 2014; Vogel et al. 2018). But the main problem for wind energy source due to intermittent nature of wind itself result in unsteady power generation and frequency deviation (Yao et al. 2011). The problem can be relieved by a plug-in hybrid electric vehicle (PHEV) to controlling power load in the system (Galus et al. 2011). However, PHEV power deviation control that was not proper charging unable to manage the real unbalance power deviation in the system and may be the reason of large frequency deviation instead (Tan et al. 2014). The PHEV power deviation control which considers the minimizations of an integral absolute error (IAE) value of the real power unbalance deviation and an IAE value of the frequency deviation is greatly desired. The PHEV proportional-integral (PI) controllers can satisfactorily restrict the frequency deviation in the isolated small power system (Senjyu et al. 2008). But efficiency method still needs to relieve the frequency deviation.

The Machine learning was a part of computational learning theory in artificial intelligence field to recognize the hidden pattern in the data and can use to optimization parameter in the process (Sra et al. 2012; Michalski et al. 2013). The main purpose of the optimization approach is to find an objective function that is a minimum or maximum (Carson et al. 1997; Liu et al. 2018). Many research applied various machine learning techniques for optimization such as simulated annealing (SA), genetic algorithm (GA), and particle swarm optimization (PSO) was already used for optimizing the controller parameters (Grefenstette. 1986; Kwok et al. 1994; Su et al. 2011). When considering the performance, GA is faster than SA because of the GA algorithm work in a parallel searching method which imitates natural genetic operation (Hasan et al. 2000). However, GA will get lower performance if the optimized function is epistatic where the parameters that will optimize was correlated (Fogel. 2006; Das et al. 2006). The GA still have the premature convergence demerit.

An artificial neural network (ANN) can apply for the PHEV controller design for damping the frequency deviation in the isolated small power system. Previously, the research to proposed new optimal controller parameters predicting the PHEV for frequency control in an isolated small power system using a neural network model (Jandum et al. 2016; Jandum et al. 2016). Moreover, the PHEV control based on the ANN can apply for controlling voltage and frequency in autonomous microgrids (Tamee et al. 2015) which the ANN was appropriately applied. However, PHEV controller parameters were best value form ANN model that cannot define in the real world. Thus we have to find the range of optimal parameters instead.

This paper focuses on an application of ANN and CI for the PHEV controller parameters optimization (ANN-CI-PHEV) considering proper PHEV charging power deviation control based on the minimizations of an IAE value of the real power unbalance deviation and an IAE value of the frequency deviation for frequency control in an isolated small power system. Simulation studies show the effectiveness and superiority of the proposed PI controllers of PHEV in comparison with the conventional PI controllers of PHEV in (Senjyu et al. 2008).

ISOLATED SMALL POWER SYSTEM

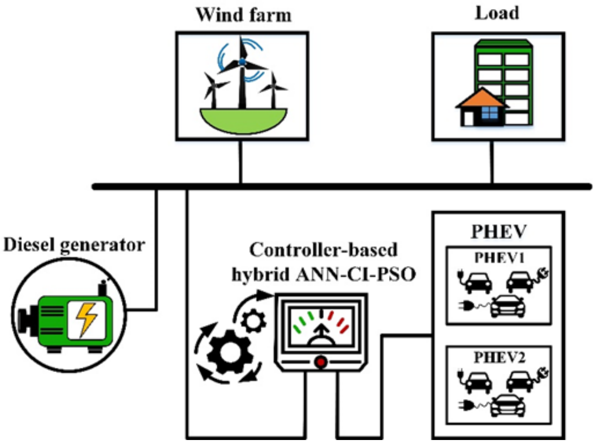

Fig. 1. The isolated small power system connected to a wind farm.

In Fig. 1, it is an isolated small power system consisting of a 20 MW diesel generator, 6 MW wind farm, 17 MW load, and 5 MW PHEV.

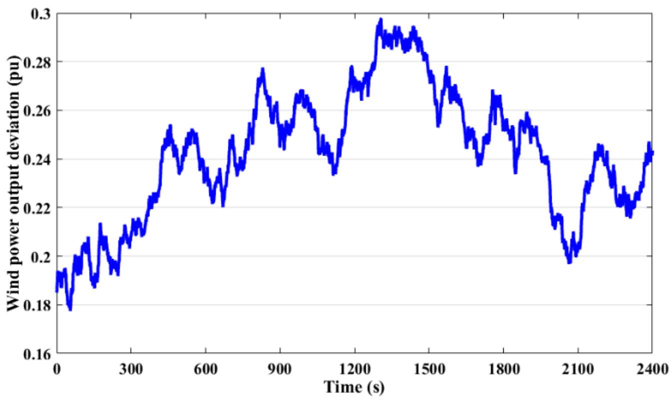

Fig. 1. The wind power output deviation.

In Fig. 2, the wind power output deviation 6 MW time under 2,400 second

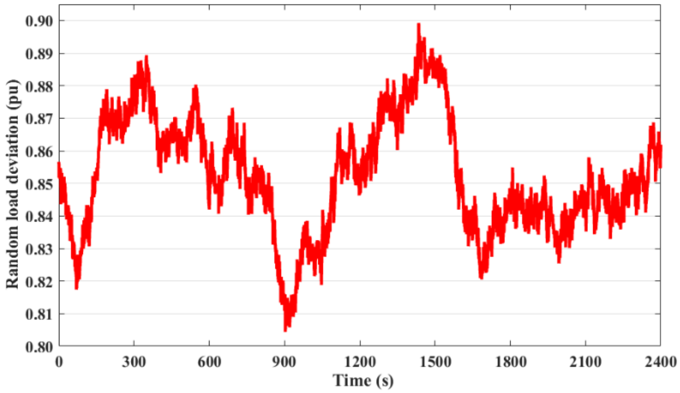

Fig. 2. The random load deviation.

In Fig. 3, the random load deviation of 17 MW time under 2,400 seconds.

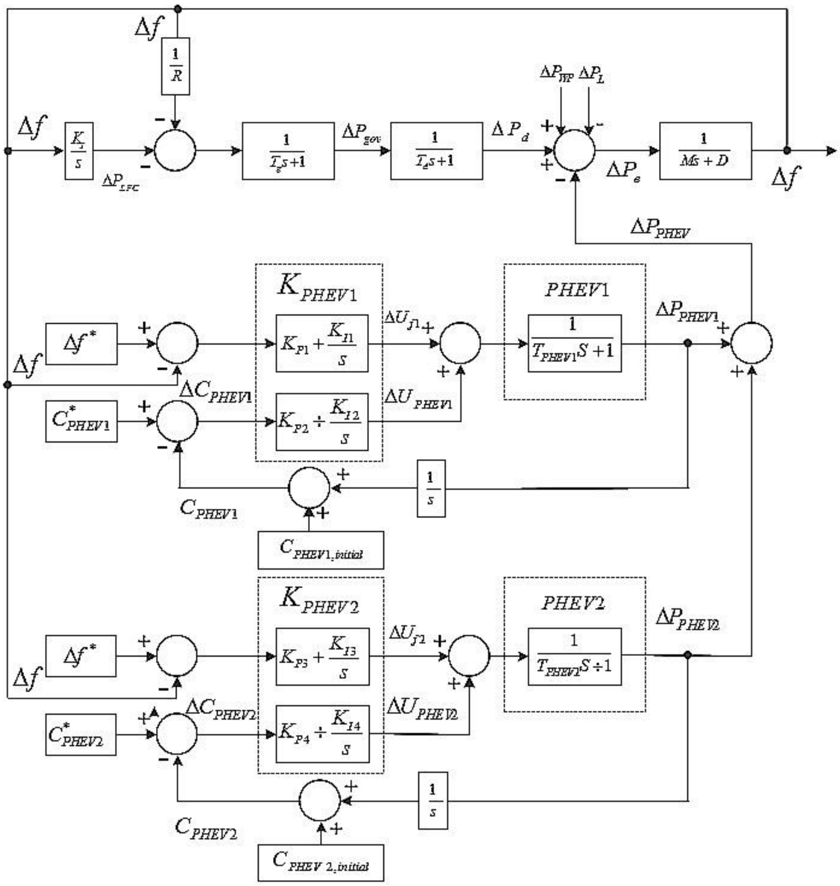

Fig. 3. The linearized model for the isolated small power system.

The linearized model of the isolated small power system is illustrated in Fig. 4. The proposed PI controllers of PHEV are

$$K_{PHEV1}(s) = K_{P1} + \frac{K_{I1}}{s}, K_{P2} + \frac{K_{I2}}{s} \quad (1)$$

$$K_{PHEV2}(s) = K_{P3} + \frac{K_{I3}}{s}, K_{P4} + \frac{K_{I4}}{s} \quad (2)$$

where the K_{PHEV1} and K_{PHEV2} are the proposed PI controllers of PHEV1 and PHEV2. The K_{P1} and K_{I1} are the PI controller parameters of the frequency deviation of PHEV1. The K_{P2} and K_{I2} are the PI controller parameters of the charging rate deviation of PHEV1. The K_{P3} and K_{I3} are the PI controller parameters of the frequency deviation of PHEV2. The K_{P4} and K_{I4} are the PI controller parameters of the charging rate deviation of PHEV2. Theis the Δf frequency deviation. The ΔP_e is the real power unbalance deviation. The ΔP_{PHEV} is the PHEV charging power deviation. The system parameter details are given in (6).

PROPOSED METHODOLOGY

In this section, we are explaining the operation in each step of using the ANN model predict the PI parameters and finding of range by confidence interval (CI) estimation as follows.

STEP 1: The ANN model predict the PI parameter

In principle, the ANN model has the power of a universal approximation and a mathematical model to simulation imitate the function of the human brain of biological nervous systems. The ANN model solves for a specific problem, such as a problem of the pattern recognition, data classification, prediction values, etc. In this phase, the ANN model is to be a predictor the PI controller parameter values of PHEV. The ANN model is varieties of kinds of network structure. The multilayer feedforward backpropagation neural network is the most popular neural networks. The neural networks are trained with a Levenberg-Marquardt (LM) algorithm and the architecture consists of the input layer, hidden layer, and output layer (Svozil et al.1997; Hagan et al. 1994) as shown in Fig. 5.

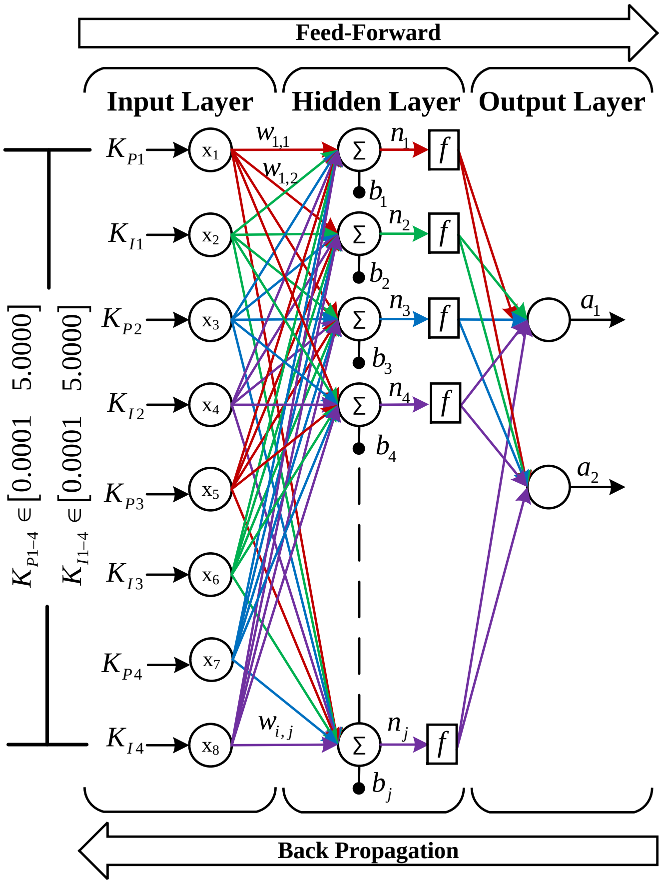

Fig. 5. The architecture of the multilayered feed-forward ANN model.

The Fig.5 shows the architecture of a multilayered feed-forward ANN model consists of an input layer, a hidden layer, and an output layer. The weight (w) and bias (b) are selected randomly in the ANN model. The w is the weight value of the connection between all the nodes of the neural network. The each of the input data are multiply by the weight matrix and set during the learning process. The b is the bias values associated with each node in the intermediate and output layers of a neural network. Get data for training, validation and test data set extract from the experiment results.

$$n_j = \sum_{i=1}^{I} w_{i,j} x_i + b_j \tag{3}$$

The n can be calculated by Equation (3) pass into an activation function determines the properties of the neuron network. The log-sigmoid function for the activation function in the ANN model. The most commonly used hidden neuron activation function is the log-sigmoid transfer function. The results of the log-sigmoid transfer function are included in a range from [0 - 1].

$$a_k = f(n) = f(\sum w_{i,n} x_n + b) \qquad \textbf{(4)}$$

The $f(n)$ is the type of activation function of the log-sigmoid transfer function. The a_k is the actual value predicted by the ANN model. The output layer data of the a_1 is an IAE value of the frequency deviation. The a_2 is an IAE value of the real power unbalance deviation. The ANN model is used to learn the linearized model of the isolated small power system and predict the minimum values of the IAE of frequency deviation and the IAE of real power unbalance deviation.

The ANN model consists of the input layer, hidden layer, and output layer. The dataset is 500 samples in the ANN model. The dataset was divided into 70%, 15% and 15% for neural network training. The 350 samples for the training set, the 75 samples for the validation set and the 75 samples for the testing set.

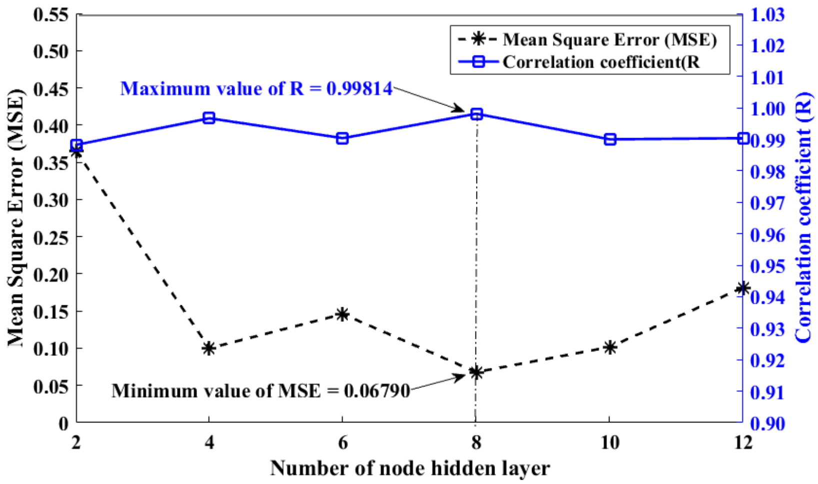

Fig. 6 The values of the mean square error and the correlation coefficient are predicted by the ANN model.

The fig. 6 shows the result of the correlation coefficient the mean square error of the number of node hidden layer. The number of node hidden layer are set as 2 to 12 and select the best of minimum value of mean square error (MSE) at number of node hidden layer at 8 for ANN model prediction the minimizations of an IAE value of the Δf and an IAE value of the ΔP_e for frequency control in an isolated small power system.

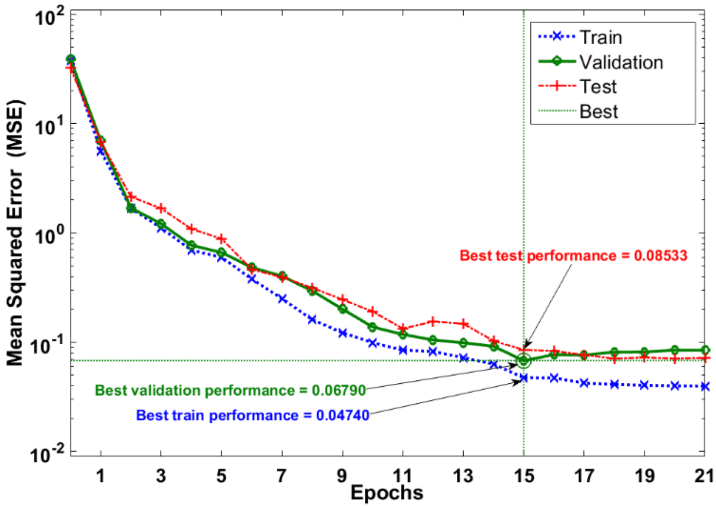

Fig. 7. The values of mean square error of the ANN model.

Fig. 7 show the MSE of the ANN model. As observed in Fig. 7, the blue graph of the best train set performance is 0.04740, the green graph of the best validation performance is 0.06790 at epoch 15 and the red graph of best test set performance is 0.08533.

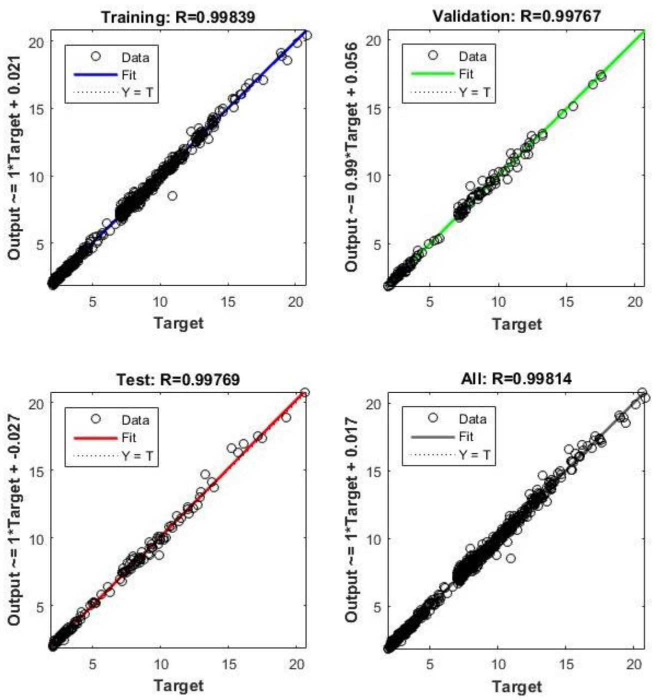

Fig. 8. The values of correlation coefficient (R) of regression plot of the ANN model.

Fig 8 exhibits the value of correlation coefficient (R) of the following regression plots display the network outputs with respect to targets for training, validation, and test sets. The values of R is 0.99814 and the slope is 1. This implies that the prediction values of the ANN model is in the same direction and achieved during the whole dataset proved that the prediction close to measured value.

The best validation performance of the ANN model for prediction of the PI controller parameters of PHEV. The random of 5,000 samples for the ANN model was applied to predict the IAE value of ΔP_e and the IAE value of Δf . The part of the group 450 samples of the random parameter can provide the result the minimum value of the IAE value ΔP_e and the IAE value of Δf . We are select the 450 sample for the CI estimation of the new lower and upper bounds of the PHEV controller parameters as shown in table 1.

Table 1. The group of 450 samples of the parameter can provide the result the minimum value of the IAE value ΔP_e and the IAE value of Δf

No.	KP1	KI1	KP2	KI2	KP3	KI3	KP4	KI4	Δf	ΔP_e
1	0.7027	0.0062	2.1019	0.0928	0.0219	0.0144	1.1342	0.8490	7.8238	1.7831
2	2.3610	0.0825	0.8114	0.0381	1.5258	0.0358	0.4165	0.0480	7.8240	1.1329
3	2.7362	0.0757	0.0104	0.0072	1.6090	0.0788	0.4322	0.0852	7.8240	1.1328
4	2.8639	0.0813	0.3400	0.0518	1.4356	0.0395	0.3524	0.0743	7.8241	1.1328
5	2.6107	0.1015	0.8569	0.0248	1.5162	0.0675	0.8960	0.0855	7.8242	1.1328
6	2.7296	0.1178	0.7391	0.0626	1.4377	0.0217	0.8169	0.0692	7.8243	1.1328
7	2.7083	0.1118	0.4883	0.0420	1.5532	0.0364	0.2639	0.0123	7.8244	1.1328
8	2.6746	0.0734	0.3914	0.0610	1.5565	0.0810	0.5883	0.0588	7.8245	1.1328
9	2.7331	0.1112	0.8594	0.0061	1.4262	0.0338	0.7217	0.0091	7.8246	1.1328
10	2.8006	0.0322	0.8121	0.0178	1.1267	0.0056	0.5633	0.0838	7.8246	1.1333
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441	2.8852	0.0497	0.8649	0.0610	1.5717	0.0629	0.2018	0.0839	7.9165	1.1165
442	2.6307	0.0329	0.7091	0.0470	1.4730	0.0018	0.4079	0.0743	7.9168	1.1165
443	2.9685	0.0784	0.5667	0.0477	1.5342	0.0269	0.7939	0.0440	7.9178	1.1162
444	2.9206	0.0521	0.7125	0.0012	1.4652	0.0125	0.2027	0.0266	7.9189	1.1160
445	2.7506	0.0472	0.7365	0.0632	1.4940	0.0254	0.8364	0.0489	7.9194	1.1160
446	2.9552	0.0587	0.0302	0.0373	1.5778	0.0148	0.4863	0.0674	7.9195	1.1159
447	2.7881	0.0533	0.8258	0.0192	1.5104	0.0222	0.3918	0.0535	7.9196	1.1159
448	2.9928	0.0580	0.6346	0.0827	1.5856	0.0649	0.5035	0.0703	7.9197	1.1159
449	2.4991	0.0408	0.3625	0.0783	1.5731	0.0010	0.8747	0.0138	7.9203	1.1158
450	2.8943	0.0533	0.2935	0.0614	1.5612	0.0069	0.1110	0.0562	7.9212	1.1156

The table 1. show the 450 sample data can provide the result the minimum value of the IAE value Δf around 7.8239 to 7.9212 and the IAE value of ΔP_e around 1.1157 to 1.7832

STEP 2: Finding of range by confidence interval (CI) estimation

The confidence interval (CI) provide more information than point estimates. The CI for means are intervals constructed using a procedure that will contain the population means a specified proportion of the time, typically either 99% of the time. The beginning of process CI is select an appropriate parameter form ANN model for population and calculate your sample mean $(\bar{x})$ and sample standard deviation (σ). The selection of the level of the confidence interval is 99% in the experiment. The (1 - α) is called the probability content or level of confidence. We are calculate the margin of error for the lower bound end of the range, subtract from the sample mean shown in equation 7. The upper bound end of the range, add from the sample mean as shown in equation 8.

$$\mathrm{P}_{Lower} = \bar{\mathrm{X}} - \mathrm{Z}_{\alpha/2}\frac{\sigma}{\sqrt{(n)}} \tag{7}$$

$$\mathrm{P}_{Upper} = \bar{\mathrm{X}} + \mathrm{Z}_{\alpha/2}\frac{\sigma}{\sqrt{(n)}} \tag{8}$$

where the Z is the value from the critical value table. The P_{Lower} called as the lower bound and the P_{Upper} called as the upper bound are generated by CI.

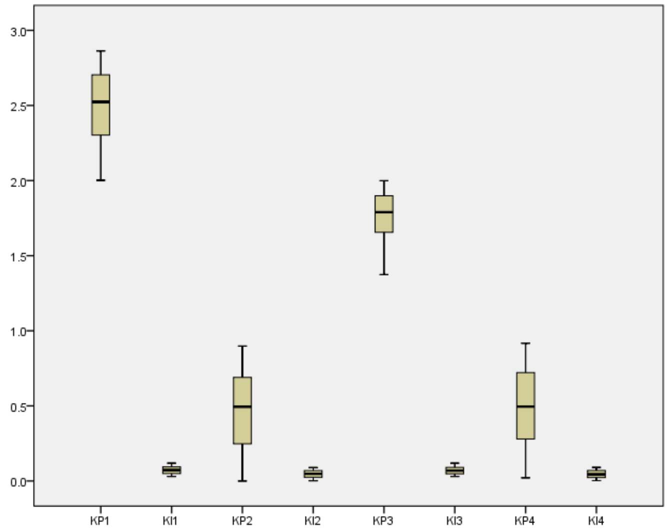

Fig. 8. The boxplot of the group of 450 samples of parameter

The Fig. 8 the simplest possible box plot displays the full range of variation from min to max of the KP1, KI1, KP2, KI2, KP3, KI3, KP4 and KI4. We use the CI finding of range lower and upper bounds are calculated by 99% of CI of the difference as shown in table 2

Table 2. The CI estimate range of parameter of PHEV

Parameter of PHEV	Test Value = 0					
	t	df	Sig.	Mean Difference	99% CI of the Difference	
					Lower	Upper
KP1	179	449	0.00	2.6341	**2.5960**	**2.6722**
KI1	55.2	449	0.00	0.0622	**0.0593**	**0.0651**
KP2	33.6	449	0.00	0.5407	**0.4991**	**0.5824**
KI2	34.17	449	0.00	0.0452	**0.0418**	**0.0487**
KP3	155.1	449	0.00	1.4900	**1.4651**	**1.5149**
KI3	31.04	449	0.00	0.0420	**0.0385**	**0.0455**
KP4	37.54	449	0.00	0.5032	**0.4685**	**0.5379**
KI4	11.55	449	0.00	0.0610	**0.0473**	**0.0747**

The table 2. show the CI estimation of the new lower and upper bounds of the PHEV controller parameters.

SIMULATION RESULTS

After the neural network model used to predict the PHEV controller parameters and then using CI estimation of the new lower and upper bounds of all parameters. Next, we randomize PHEV controller parameters values three samples and replaced in the equations (1) to (2).

The proposed PI controllers of ANN-CI-PHEV-1 (parameters values samples one) can be obtained as follows:

$$K_{ANN-PHEV1}(s) = 0.7027 + \frac{0.0062}{s}, 2.1019 + \frac{0.0928}{s}$$
$$K_{ANN-PHEV2}(s) = 0.0219 + \frac{0.0144}{s}, 1.1342 + \frac{0.8490}{s}$$

As a result, the proposed PI controllers of ANN-CI-PHEV-2 (parameters values samples two) are

$$K_{PSO-PHEV1}(s) = 1.0027 + \frac{0.0062}{s}, 2.9879 + \frac{1.9067}{s}$$
$$K_{PSO-PHEV2}(s) = 0.0229 + \frac{0.0142}{s}, 2.8298 + \frac{1.1256}{s}$$

As a result, the proposed PI controllers of ANN-CI-PHEV-2 (parameters values samples three) are

$$K_{ANN-CI-PSO-PHEV1}(s) = 2.0476 + \frac{0.0399}{s}, 0.0647 + \frac{0.0124}{s}$$
$$K_{ANN-CI-PSO-PHEV2}(s) = 1.1021 + \frac{0.0454}{s}, 0.0762 + \frac{0.0196}{s}$$

Table 3. The IAE value of frequency deviation and the real power unbalance deviation.

Methodology	The frequency deviation (Δf)	The real power unbalance deviation (ΔP_e)
Conventional- PHEV	12.2220	3.0313
ANN-CI-PHEV-1	7.4341	1.8688
ANN-CI-PHEV-2	3.1037	1.2874
ANN-CI-PHEV-3	6.4868	1.6944

Accordingly, the table 3 shows both the IAE value of frequency deviation (Δf) and the real power unbalance deviation (ΔP_e). The values of IAE Δf in the case of the Conventional-PHEV is 12.2220, ANN-CI-PHEV-1 is 7.1341, ANN-CI-PHEV-2 is 3.1037. Also, the IAE value Δf in the case of the ANN-CI-PHEV-3 is 6.4868. The values of IAE of ΔP_e in the case of the Conventional-PHEV is 3.0313, ANN-CI-PHEV-1 is 1.8688 and ANN-CI-PHEV-2 is 1.2874. Also, the IAE value of ΔP_e in the case of the ANN-CI-PHEV-3 is 1.6944. The IAE value of frequency deviation (Δf) and the real power unbalance deviation (ΔP_e) of the proposed ANN-CI-PHEV is much lower than the Conventional-PHEV.

Fig 9-10 show the simulation of the ANN-CI-PHEV are compared with conventional PI controllers of PHEV (Conventional- PHEV)

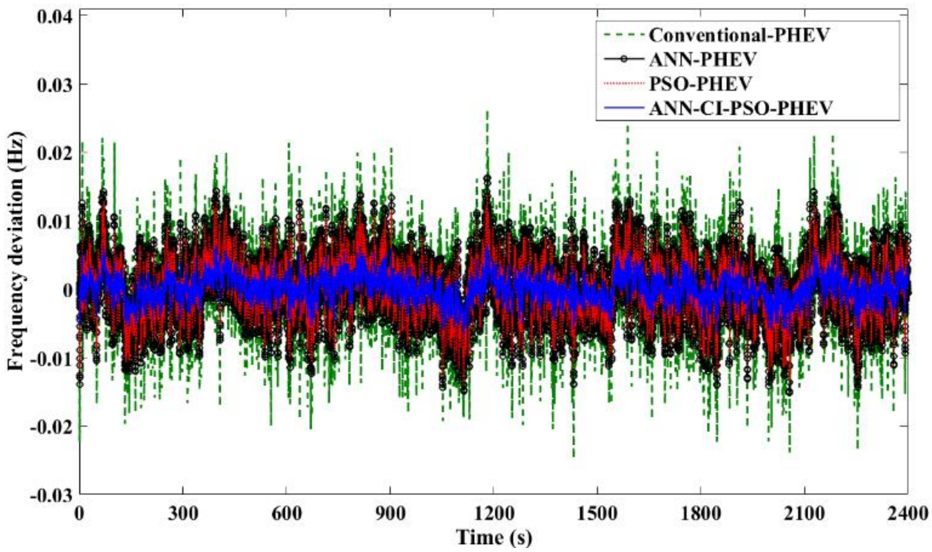

Fig. 9. Frequency deviation (Δf)

Fig 9 shows the frequency deviation (Δf) in the isolated small power system. The green graph dotted line is the Conventional-PHEV. The black graph is the ANN-CI-PHEV-1. The red graph dotted line is the ANN-CI-PHEV-3. The blue graph line of ANN-CI-PHEV-2. The proposed ANN-CI-PHEV can suppress greatly the frequency deviation when compared with the Conventional-PHEV.

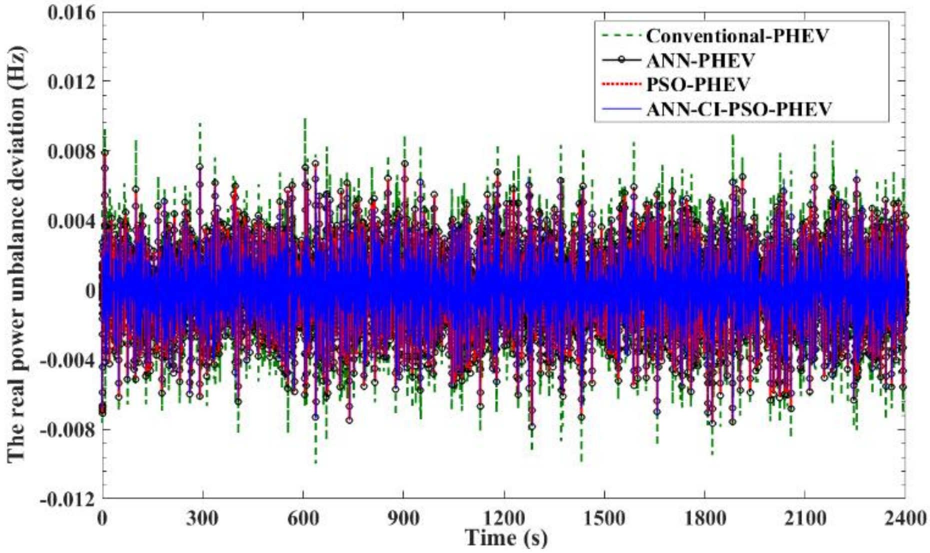

Fig. 10. The real power unbalance deviation (ΔP_e)

Figure 10 shows the frequency deviation in the isolated small power system. The green graph dotted line is the Conventional-PHEV. The black graph is the ANN-CI-PHEV-1. The red graph dotted line is the ANN-CI-PHEV-3. The blue graph line of ANN-CI-PHEV-2. The proposed ANN-CI-PHEV can suppress greatly the real power unbalance deviation when compared with the Conventional-PHEV.

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CONCLUSIONS

The ANN-CI-PHEV for the PHEV controller parameters optimization considering proper PHEV charging power deviation control based on the minimizations of an IAE value of the real power unbalance deviation and an IAE value of the frequency deviation for frequency control in an isolated small power system. For the PHEV controller structure, it is a PI. Simulation studies show the effectiveness and superiority of the proposed PI controllers of PHEV in comparison with the conventional PI controllers of PHEV, the ANN-CI-PHEV designed by neural network model and find the range of PHEV controller parameters using the confidence interval (CI) estimation from prediction. This illustrates that the new proposed method is able to effectively find both the minimum IAE value of Δf and the minimum IAE value of the ΔP_e.

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