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Power factor correction: performance comparison of an existing microcontroller-based system and a neuro-fuzzy system

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Abstract

An existing microcontroller-based power factor correction system has been able to improve the overall conversion of electrical power into a useful work of a highly industrial load. However, more improvements are still desired to get the existing power factor value close to 1 as much as practically possible. With the current microcontroller-based power factor correction system, microcontroller has to be replaced often due to power fluctuation and a low-quality power available. The microcontroller requires ordering for new replacement as it is not reprogrammable to meet the new operational demands. Artificial intelligence tools, neural network and fuzzy logic are considered. Neuro-fuzzy system approach is settled for as an alternative to microcontroller-based power factor correction system. Neuro-fuzzy system is able to learn through training, testing, and validation processes and controls the automatic switching of the capacitor banks to adequately compensate for the lagging loads. Results obtained were compared to the existing microcontroller power factor correction system. Neuro-fuzzy system shows better performance over microcontroller-based system. The neuro-fuzzy system automatically adjusts itself to suit the present operational requirement to always have a power factor result closer to 1 as compared with that of a microcontroller-based system which does not give room for reprogramming making it static to a larger extent in its operational duties.

1. Introduction

It is desired that electrical power being delivered to any systems be fully converted into a useful work. This is the role that power factor (PF) plays in measuring on a scale of 0 to 1, how effectively electrical power has been converted into a useful work [1]. “1” being fully converted and shows perfect systems [2]. However, such is not always the case in practice due to inductive loads that generate reactive element that make power lag [3]. To mitigate the effect of lag loads, capacitor banks are introduced into the system to provide a leading effect in order to raise the value of power factor to a value that is 1 or closer to 1 [4]. The introduction of capacitor banks into the system for compensation is to be done sequentially to ensure adequate balance in the operation of the system [5, 6]. So, adequate switching technique is to be adopted into the system either manually or automatic [7]. For a manual approach, it involves a human operator who engages or disengages the capacitor banks one after the other into or from the system depending on the power factor value as obtained from the overall system [8].

On the other hand, automatic switching technique is adopted to automatically engage or disengage the capacitor banks as the PF correction system in which the microcontroller acts as the reasoning and decision-making faculty of the system [9]. It continuously measures the power factor value and engages or disengages the capacitor banks seamlessly using relays as the switching mechanism. Many automatic power factor correction topologies run using microcontrollers as they have proven to be stable, reliable, and efficient. However, microcontroller, once programmed cannot be reprogrammed again [10]. This is an important factor that needs to be looked into as power system is dynamic in nature and therefore requires implementation of changes. Also, microcontrollers are susceptible to damage by static charge [11]. So, in an environment that experiences low-power quality, longevity of microcontroller is in doubt and could fail at any time [12]. These and many more of these vulnerabilities of a microcontroller led to seeking an alternative in artificial intelligence (AI) based on its capabilities and flexibility in areas of applications [13, 14].

Remarkable results have been achieved with the use of artificial intelligence tools in power systems [15]. From power generation to power transmission. From power transmission to power distribution. From power distribution to end users. So, with AI having proven to be smart and efficient with many possibilities, its tools that are suitable for power system applications are considered in this work [16, 17]. The intelligent and learning capabilities of neural networks and the decision-making capacity of fuzzy system were combined in neuro-fuzzy system that formed the basis for its performance investigation in the area of power factor correction which is the focus of this work [18, 19, 20]. The neuro-fuzzy results would be compared with the existing microcontroller-based system results. The rest of the paper contains materials and methods, results and discussion as well as conclusions.

2. Method

Generally, the relationship amongst real power, apparent power, and reactive power is represented by "power triangle" of Figure. 1. The red line is the active power, P (W). The green line is the apparent power, S (VA). The purple line represents the reactive power, Q (var).

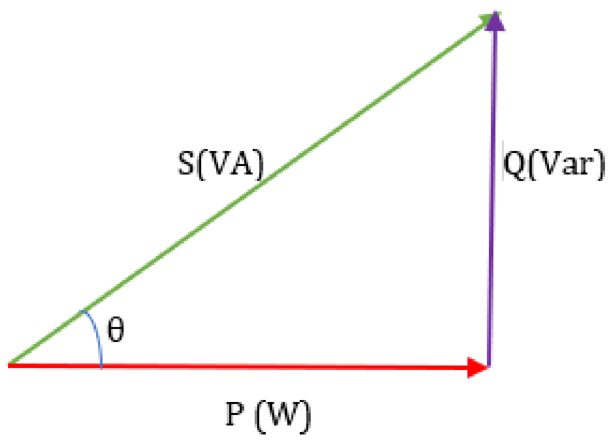

Figure 1. Power triangle

Mathematically [4],

$$P = VIcos\theta \quad (1)$$

$$S = VI = P + jQ \quad (2)$$

$$Q = VIsin\theta = P\sqrt{(\frac{1}{pf^2} - 1)} \quad (3)$$

where,

V is the root mean square voltage. I is the root mean square current.

Θ is the phase angle between the real power and the apparent power.

$$Power\ factor, pf = \frac{P}{S} = cos\theta \quad (4)$$

2.1. Existing Microprocessor-based System

The existing microcontroller-based power factor system of Figure 2 makes use of the configuration above to aid the automatic switching operations of the capacitor banks. The NCP1681 is the microcontroller utilized and operates in Boundary Conduction Mode (BCM), Continuous Conduction Mode (CCM), and Discontinuous Conduction Mode (DCM) being a multi-mode engine. For high-power applications and to keep CCM, mode change is inhibited [21].

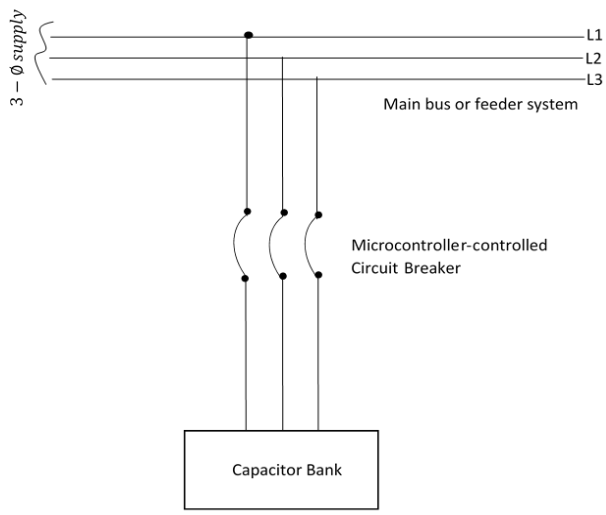

Figure 2. Existing microcontroller operations at high power mode

2.2 Neuro-fuzzy Approach

The neuro-fuzzy model used is of two inputs parameters and one output parameter as shown in Figure 3. The membership functions of the two inputs, that is, real power and reactive power used to determine the power factor at various loads are presented in Figures 4 and 5 respectively. Normalization of data to values between 0 and 1 was carried out using adapted data linearization model [22].

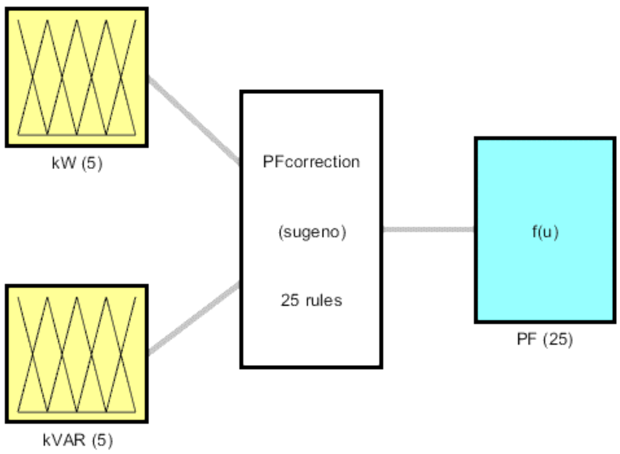

Figure 3. Fuzzy inference system used

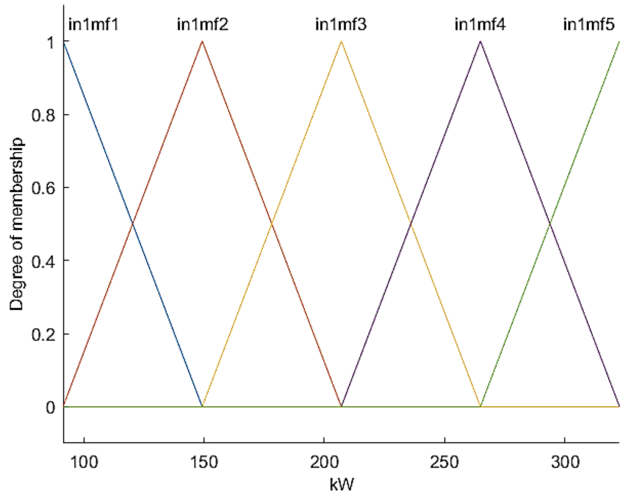

Figure 4. Real power membership functions

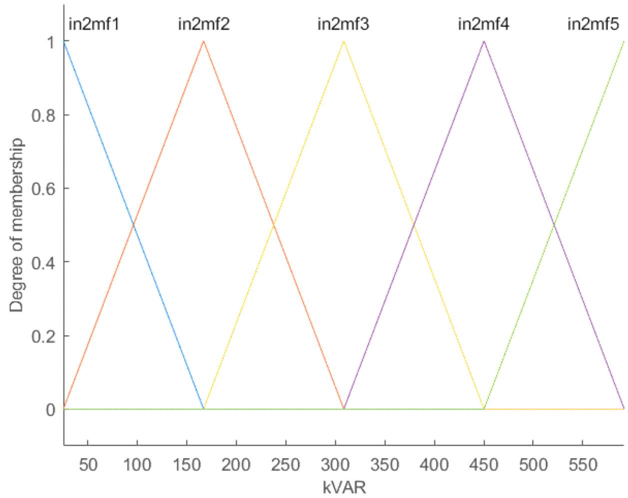

Figure 5. Reactive power membership functions

The applied rules were 25 utilizing the "if-then" logic as represented mathematically by Eqs. (5) and (6). $\mu_{A \cup B}(x) = \max[U_A(x), \mu_{\boldsymbol{B}}(x)]$ (5)

The union and intersection of the two input in relation to the output is given by Eqs. (6) and (7).

$$\mu_{A\cup B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x)$$

$$\mu_{A\cap B}(x) = \mu_A(x)\mu_B(x)$$

$$\mu_{A \cup B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x) \quad (6)$$

$$\mu_{A \cap B}(x) = \mu_A(x)\mu_B(x) \quad (7)$$

where A and B are two subset of U which represent the truth of A and B.

Linear normalization technique was utilized to convert the parameters between 0 and 1 using the adapted model of Eq. 8.

$$x_i^*(k) = \frac{\max x_i(k) - x_i}{\max x_i(k) - \min x_i(k)} \quad (8)$$

where i = 1, 2, 3, …, m and k = 1, 2, 3, …, n. m and n are parameters used for the experiment and corresponding outputs.

$x_i(k)$ and $x_i^*(k)$ are the original sequence and the sequence post data pre-processing. $\max x_i(k)$ is the largest value of $x_i(k)$ and $\min x_i(k)$ is the smallest value of $x_i(k)$.

Eq. (8) justifies Fig.ure 6 which is used to determine the fuzzy rules from the training data by the neural network before initialization of data.

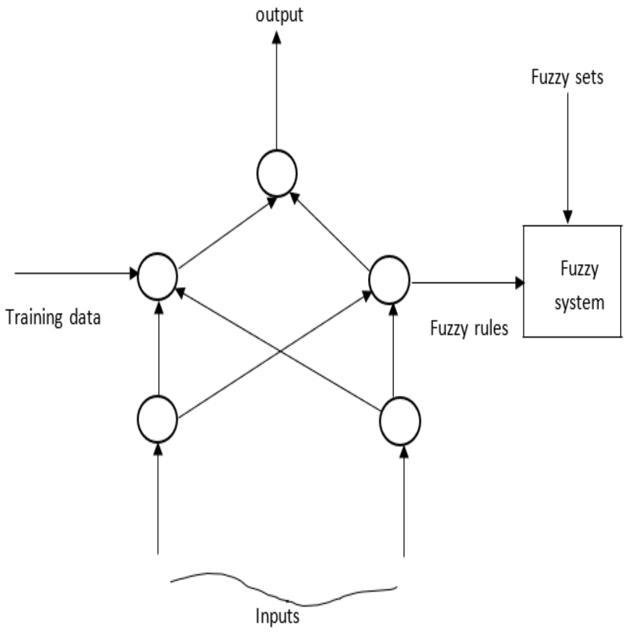

Figure 6. Cycle of the fuzzy rules using the training data

Once the rules were established, the outputs combined with the neural network system to complete the neuro-fuzzy processes as presented in Figure 7. This system was utilized in the automatic switching of the capacitor banks in response to the changes in power factor value of the loads. Decisions of the neuro-fuzzy system were fast and prompt in response to the target power factor value that the entire system is aiming to achieve and maintain. The neuro-fuzzy model structure is presented in Figure 8 and the training sequence is shown in Figure 9 with the blue nodes depicting the "and" rules that were utilized.

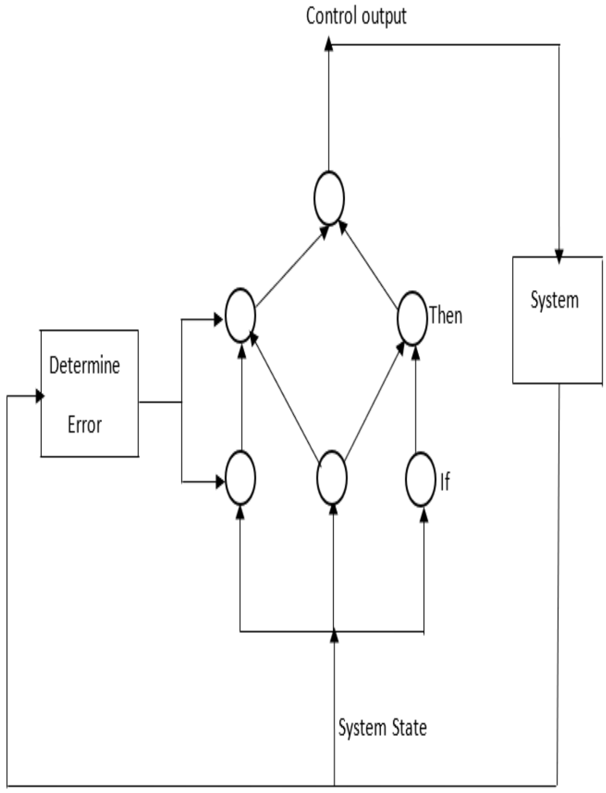

Figure 7. Neuro-fuzzy system operational flow

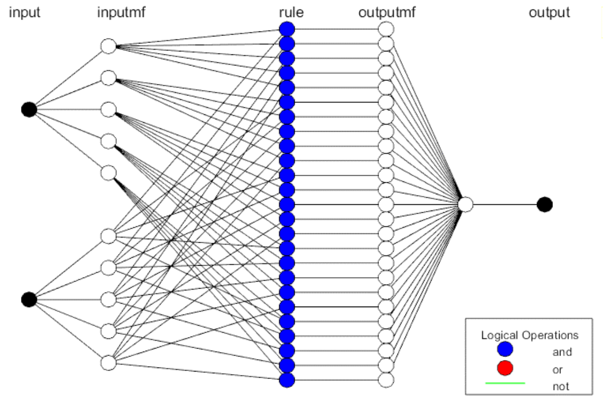

Figure 8. Neuro-fuzzy structure

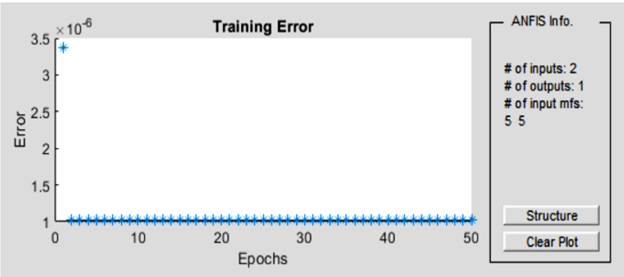

Figure 9. ANFIS training session

3. Results

For the measured real power and apparent power measured for various load points that were connected to the power supply, the existing microcontroller system power factor readings and the corresponding neuro-fuzzy power factor outputs are presented in table 1. These simulated results were obtained using MATLAB R2018a software platform.

Table 1. Microcontroller power factor results and neuro-fuzzy power factor results

Real Power (W)	Apparent Power (VA)	PF of Microcontroller Output	PF of Neuro-fuzzy Output
124.95	117.247	0.9381	0.999622288
97.1196	91.4091	0.92309	0.950057207
128.653	99.1362	0.95511	0.854444993
672.3899	322.79	0.47503	0.556639373
673.2517	321.027	0.47941	0.535673904
1230.03	997.473	0.81447	0.809634985
1242.4317	1014.44	0.81521	0.823725906
1229.5057	1006.17	0.8198	0.817780017
1255.62	1001.94	0.80914	0.807493487
1253.92	1005.74	0.80499	0.812270472
1222.69	989.757	0.80525	0.805138557
1164.25	942.786	0.80747	0.811584866
1169.15	944.67	0.80777	0.808344257
585.823	280.203	0.47992	0.443998101
1193.5	934.042	0.78835	0.783152638
1224.87	998.963	0.79614	0.812419737
1235.95	998.509	0.80924	0.808952125
1248.55	1005.91	0.80843	0.813581935
667.52	329.62	0.80944	0.642951446
1204.77	987.64	0.80964	0.810113083
1216.78	988.67	0.80554	0.80638964
1214.64	986.491	0.80963	0.805479188
1219.33	986.681	0.80874	0.803809447
1214.9	973.124	0.80865	0.794915801
1214	983.489	0.80905	0.803404028
656.625	308.708	0.46277	0.469095241
643.571	309.198	0.48115	0.520336879
1151.72	898.396	0.8005	0.813053681
95.0875	89.1937	0.94266	0.944496379
93.7079	88.3105	0.9418	0.945016668
92.2514	87.0201	0.945	0.943122177
99.7175	93.751	0.9431	0.953854538
654.699	311.945	0.4917	0.508588351
1210.64	977.773	0.81342	0.800560502
132.178	180.128	0.69094	1.412340956
97.874	147.192	0.65931	1.331226547
105.953	153.383	0.65732	1.338296405
101.703	159.697	0.64664	1.400751175
110.19	165.231	0.6455	1.402182753
105.042	147.977	0.71472	1.304796933
105.14	146.415	0.71704	1.293520336
100.08	143.265	0.7304	1.294274041
147.628	214.092	0.68935	1.590544424
144.093	209.995	0.69353	1.575566963
160.655	237.934	0.6691	1.710665204
164.807	245.394	0.64663	1.74868722
150.609	231.057	0.63957	1.700632688
145.947	227.337	0.66294	1.692449326
133.43	216.7	0.68875	1.666841162
125.795	196.333	0.68923	1.553958418
130.897	190.801	0.66965	1.493466057
141.394	199.768	0.67535	1.513482898
129.354	190.958	0.67794	1.501059238
151.702	217.22	0.68774	1.596520184
153.71	212.228	0.66775	1.552336947
130.899	221.431	0.68555	1.710650974
140.26	222.375	0.66644	1.679703641
149.862	216.043	0.68881	1.595500532
947.532	1302.95	0.73014	0.861452395
959.501	1291.15	0.71554	0.859922941
947.321	1301.09	0.72554	0.861479357
945.6	1290.78	0.72471	0.861699271
96.7324	125.671	0.74236	1.187978109
102.506	130.406	0.77115	1.19438304
100.203	125.263	0.77656	1.169299893
100.302	125.792	0.78725	1.172503579
334.311	815.24	0.41326	1.763595357
862.305	1224.14	0.69254	0.872341853

The output from the neuro-fuzzy system is shown in Figure 10 which typically shows the power factor value per real power and reactive power.

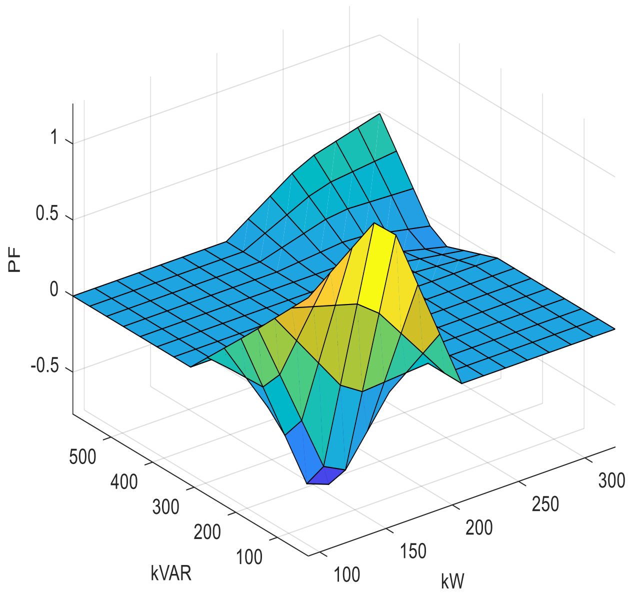

Figure 10. Neuro-fuzzy system output

The measured power factor value of the microcontroller-based system against designated system nodes is shown in Figure 11. Also, the outputs from the neuro-fuzzy system from designated power system nodes are displayed in Figure 12 as well. Figure 13 draws the comparison between the power factor outputs of the microcontroller-based system and the neuro-fuzzy based system.

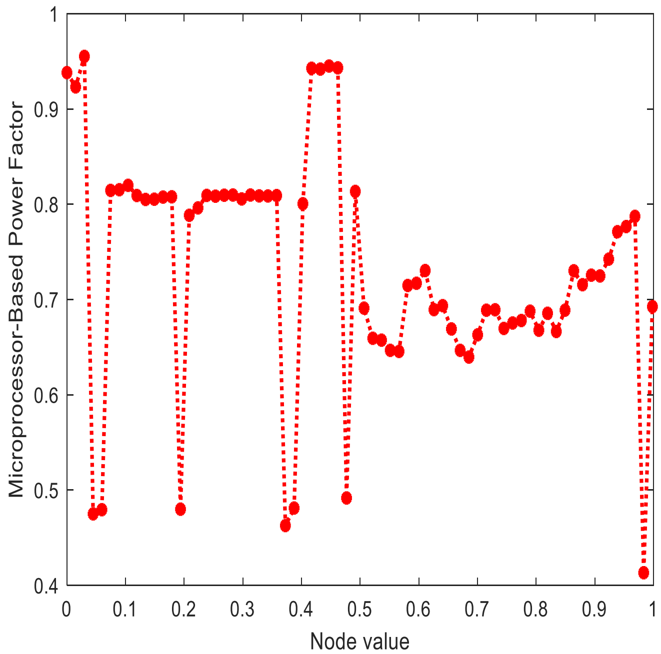

Figure 11. Power factor results from microcontroller-based system

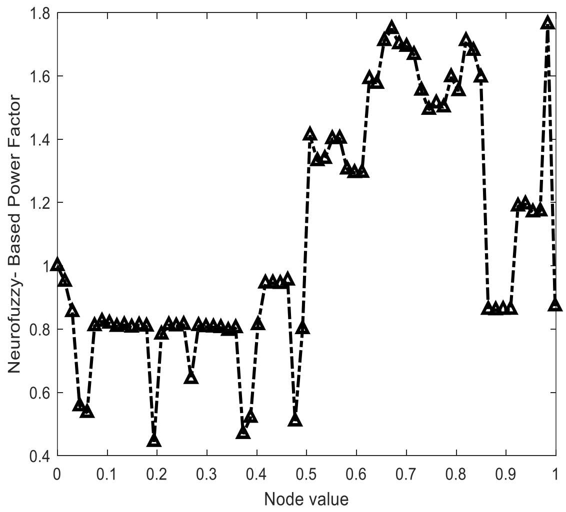

Figure 12. Power factor results from neuro-fuzzy system

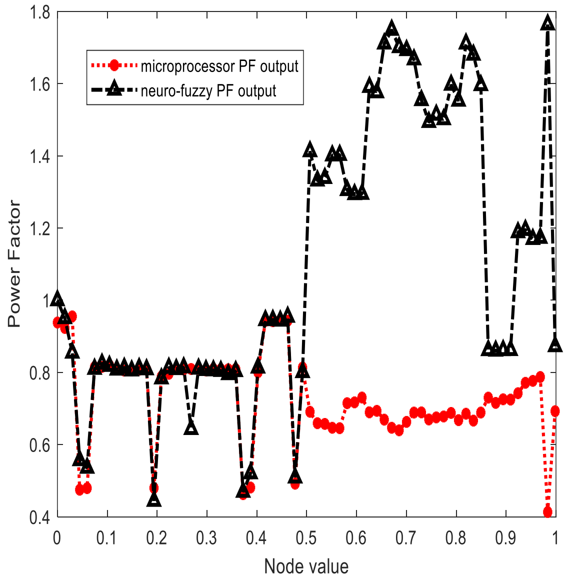

Figure 12. Microprocessor PF (in-red colour) and Neuro-fuzzy PF compared (in-black colour)

4. Discussion

The neuro-fuzzy system model structure for the engagement of the capacitor banks switching operation targets a desired power factor value of 0.9 at least. This model consists of a 5-layer structure with 2-input and 1-output. The two inputs were combined to form a 25-rule operational set. This acts as the decision faculty of the operations. The input data used for the neuro-fuzzy system were trained using grid partitioning technique in order to ensure smooth and continuous uniqueness of each data. Issues of overshadowing is thereby prevented. It also allows for error tolerance. An error value of 0.050691 was recorded at 50 epochs as displayed in Fig. 9. From the neuro-fuzzy power factor results, it could be observed that system responded to steep rise in real power between 100 kW and 225 kW as depicted between node 0.1 and 0.5 trying to maintain the target value of at least 0.9. A sharp rise in power factor value was experienced by the system above the value of 1 at values above 250 kW followed by the system response to maintain the target value of 0.9 as shown between node 0.8 and node 0.9.

A sharp drop was noticed in power factor value between nodes 0.9 and 1 bringing the power factor value to the target value of 0.9. This is an indication that the neuro-fuzzy system has gained the required experience in making its decisions for onward control of the switching actions of the actuator connected to the capacitor banks. A quick check of Figure 12 clearly shows that neuro-fuzzy power factor correcting system surpasses microcontroller-based power factor correcting system at heavy loads. As load increases, the better the performance of neuro-fuzzy power correcting system in maintaining the target power factor value of 0.9 unlike the microcontroller-based power correcting system that struggled at higher loads.

This neuro-fuzzy system takes over at higher loads to efficiently deliver the 0.9 power factor which is the desired value. A power factor monitoring sensor constantly monitors the micro-controller output. This switching operation ensures dynamic switching of capacitors and/or inductors as load conditions change in the system. In this manner, precision in terms of reactive power compensation is guaranteed. The background artificial intelligence tool is neuro-fuzzy logic and the hardware tool implementation could be realized using 8-bit Motorola 68HC711E9 microcontroller. Windows V5 could be used as the compiler. This hardware device is suitable to handle power factor correction duty.

5. Conclusion

This work has presented a neuro-fuzzy approach to improving the power factor of an industrial power system. This approach has brought about automatic operations of the switching action of the capacitor banks to compensate for the lagging current present in the system due to inductive loads that are prevalent in industrial power systems. The obtained results due to neuro-fuzzy system show an improved performance over the existing microcontroller-based power factor correction system especially at heavy loads. Improvement in the associated gains in terms of reduction in power consumption rate, economic gain, and smooth equipment performance leading to increase in their life span could be achieved by using neuro-fuzzy power factor correction system over microcontroller-based power factor correction system.

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Author contributions

Philip Adewuyi: Writing-Original draft preparation, Methodology, Software, Writing-Reviewing and Editing.
Gbenga Adebajo: Conceptualization, Data curation, Validation, Investigation.

Conflicts of interest

The authors declare no conflicts of interest.

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