Performance enhancement of grid-interfaced inverter using intelligent controller

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Abstract
The high-performance grid-interfaced inverters are in demand as they are rapidly used in renewable energy systems. The main objective of grid-interfaced inverters is to inject high-quality active and reactive power with sinusoidal current. Many control schemes have been proposed earlier in the literature, but the operation under parametric uncertainties has not been given much attention. In this article, an adaptive network–based fuzzy inference control algorithm for a three-phase grid-interfaced inverter under parametric uncertainties is proposed. The main purpose of the proposed technique is to enhance the response time, decrease the steady-state oscillation in the injected active and reactive power and enhance the power quality even with parametric uncertainties. For assessment and evaluation reason, the conventional proportional–integral control is compared with the proposed controller. For a fair comparison, the gain setting for the proportional–integral control is obtained by Particle swarm optimization algorithm. The suggested system is developed and simulated in MATLAB/Simulink. Simulation results demonstrate that both the controllers work well to regulate the powers to required values, even with parametric variations. However, the proposed control demonstrates superiority in comparison to conventional proportional–integral control in terms of speedy response, decreased steady-state fluctuations, better power quality and increased robustness. The rise time and fluctuations in the per-unit active and reactive power are much less with the proposed control. Total harmonic distortion of the injected current and grid current are significantly better than the conventional proportional–integral control.

Keywords
Renewable energy sources, grid connected inverter, ANFIS, power quality, active and reactive power control

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Introduction
The use of high-performance grid-interfaced inverters is the need of time as the renewable energy sources (RESs) are being connected to the distribution system using these inverters. The integration of RESs to the grid poses many challenges in spite of substantial growth in the technologies of power generation. Inverters are the most suitable interface medium to connect the alternative energy sources with the existing grid.¹ The main objective of grid-interfaced inverters is to inject high-quality active and reactive power with sinusoidal current. A large number of control techniques for three-phase grid-interfaced inverters can be found in the texts for the interfacing inverters,²–⁸ but the operation under parametric uncertainties has not been given much attention. The inverter can also used as active power filter in distribution grid. In addition to improve power quality, active power filter can be used to control bidirectional power flow and thus serves as a multifunctional compensator. In Sawant and Chandorkar,⁹ a multifunctional compensator is proposed to compensate harmonics, reactive power and to eliminate source neutral current using the instantaneous p–q–r theory. In Singh and Arya,¹⁰ the inverter is used as a DSATCOM. Reference signals are constructed on correlation and cross-correlation function strategy. Power control scheme is used in He et al.¹¹ to generate fundamental current reference by the grid-interfaced inverter to mitigate harmonics. The two independent control loops are used: one is used to control the fundamental component and other one to control the distributed generation (DG) harmonic current. Voltage-oriented control is a popular method in the

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control of grid-interfaced converters. These methods use transformation of active and reactive components of currents into synchronously rotating reference frame. Modulation blocks are used to generate the switching signals resulting into constant switching frequency. Voltage-oriented control with proportional–integral (PI) control is the most favoured technique in permanent magnet synchronous generator–based wind energy sources, but regulating the gains of PI control is a major drawback. Thus, the performance is influenced by the system parameter variations. Another control algorithm based on direct torque control of AC machines known as direct power control (DPC) has been benchmarked for grid-connected converters. The hysteresis comparators are used as regulators to minimize error of instantaneous active and reactive power. No modulation blocks are required, but the switching frequency is not constant. So, it becomes difficult to design the filters. Another drawback is that this method causes ripples in active and reactive powers at steady state. In Hu et al., DPC and sliding mode approach are used along with space vector modulation (SVM) to adjust the instantaneous active and reactive power of grid-interfaced inverter. It avoids the use of current control loops and achieves independent control of active and reactive power. The SVM helps to attain constant switching frequency. However, it results into poor adaptability to dynamic systems. Nonlinear backstepping control algorithm for back-to-back connected voltage source converters is proposed in Errami et al., which is more rugged and less sensitive to parameter variations.

To incorporate dynamical systems, neural network approach is used by the author to control a grid-interfaced bidirectional converter. The traditional PI controller can reduce the small oscillations, but the PI gains are well founded only around a certain operating point. The PI gains need to be tuned to variations in system parameters. Self-tuning may be an option for improvement in dynamic response of any system. But realization of self-tuning PI controller is not easy and is time-consuming. The alternative is to use intelligent techniques like fuzzy logic and neural networks. The fuzzy logic control (FLC) is simple rule-based approach for non-linear and vague systems. FLC does not respond to the slow changes in their surroundings and no efficient method is available to tune the parameters. However, the fuzzy controller can be made adaptive and is named as adaptive network–based fuzzy inference system (ANFIS). ANFIS has manifested the improvement in damping of the oscillations.

The ANFIS is the union of two intelligent techniques, that is, artificial neural networks (ANN) and FLC. ANFIS has the potential of the learning capability of ANN with the fuzzy understanding of the FLC system. ANFIS is used to control three-phase hybrid power filter comprising an active filter with C-type high-pass filter to compensate harmonics in Bett et al. Maximum power point tracking algorithm is applied using ANFIS by the author and accurate results with very fast response are obtained in Hunoor and Savanur. The author in Thao and Ouchida has used two techniques to control the active and reactive power fed into the grid by a photovoltaic inverter. One is the direct feedback linearization (FBL) and another one is the mixture of the FBL with fuzzy logic (FBL-FL). The author has used ANFIS control to adjust the active and reactive power of induction generator by injecting rotor voltage. The author in Sai Seshu Babu and Shanmukha Sriman has used ANN control to achieve speedy dynamic behaviour by the grid interfaced converter.

An adaptive network–based fuzzy inference control algorithm is used to control a grid-interfaced three-phase inverter in this article. The main purpose of the proposed scheme is to enhance the response time, decrease the steady-state oscillation in the injected active and reactive power and enhance the power quality even with parametric uncertainties. For assessment and evaluation reason, the conventional PI control is compared with the proposed controller. For fair comparison, the gain setting of PI control is obtained by Particle swarm optimization (PSO). The PSO is simple, can be easily realized, more rugged to control parameters and has high computational effectiveness. The active and reactive power is used as control variables and average power control method is used to generate current reference. The current references are in the form of d-axis and q-axis currents. ANFIS-based controller is used to track the currents to the reference values, which in turn control the active and reactive powers. The proposed system is developed and simulated in MATLAB environment. As the variation in the parameters of filter and transformer may affect the performance of the system, it is important to validate the performance of the system with the parametric uncertainties. Both the PI and ANFIS-based controllers are simulated with the parametric uncertainties also. Simulation results demonstrate that both PI- and ANFIS-based controls work efficiently to regulate the active and reactive power to desired values, even with parametric uncertainties. However, the ANFIS-based control shows superiority in comparison to conventional PI control in terms of fast response, decreased steady-state fluctuations, better power quality and increased robustness.

The remaining part of this article is organized as follows. The model of grid-connected inverter is described in section ‘Model of grid-connected inverter’. The proposed control topology is presented in section ‘Development of control algorithm’. The PSO algorithm is presented in section ‘PSO’. The ANFIS control design and training principle are presented in section ‘Design of ANFIS controller’. Section ‘MATLAB simulation results’ presents the MATLAB simulation. The simulation results are presented under conditions of non-parametric uncertainties and with parametric uncertainties. In addition, the proposed ANFIS-based control is compared with conventional PI control. Finally, conclusion is drawn in section ‘Conclusion’. 552
The per-unit system is used to simplify the control scheme as it will ease in determining and tuning the controller coefficients. The mathematical model based on the per-unit (pu) system is defined as follows

\[ V_{pu} = \frac{250}{\sqrt{3}} V; I_{pu} = \frac{268}{\sqrt{3}} A \]  

(2)

\[ V_{pu} = 10 kV; I_{pu} = \frac{6.7}{\sqrt{3}} A \]  

(3)

\[ Z_{pu}^b = \frac{V_{pu}^b}{I_{pu}^b} = 0.932 \Omega; S_{pu}^b, 3ph = 67 kV A \]  

(4)

The different per-unit values can be computed as

\[ v_{id}(pu) = \frac{v_{id}}{I_{pu}}; v_{iq}(pu) = \frac{v_{iq}}{I_{pu}} = \frac{(v_{duo})}{I_{pu}} \]  

(5)

\[ i_{id}(pu) = \frac{i_{id}}{I_{pu}} = \frac{(i_{ Luo})}{I_{pu}}; i_{iq}(pu) = i_{iq}(pu) \]  

(6)

\[ R_T(pu) = \frac{R_T}{Z_{pu}^b}; L_T(pu) = \frac{2\pi f_L L_T}{Z_{pu}^b} = 120\pi L_T Z_{pu}^b \]  

(7)

The equation for the three phases can be written from equation (1), using equations (5)–(7) in per-unit system as in the following

\[ \begin{bmatrix} v_{id}(pu) \\ v_{iq}(pu) \\ v_{pu}(pu) \end{bmatrix} = R_T(pu) \begin{bmatrix} i_{id}(pu) \\ i_{iq}(pu) \end{bmatrix} + L_T(pu) \frac{di_{id}(pu)}{dt} - \omega_L L_T(pu) i_{iq}(pu) + v_{gd}(pu) \]  

(8)

Equation (8) can be written in rotating dq reference frame as in the following

\[ v_{id}(pu) = R_T(pu)i_{id}(pu) + L_T(pu) \frac{di_{id}(pu)}{dt} - \omega_L L_T(pu)i_{iq}(pu) + v_{gd}(pu) \]  

(9)

\[ v_{iq}(pu) = R_T(pu)i_{iq}(pu) + L_T(pu) \frac{di_{iq}(pu)}{dt} - \omega_L L_T(pu)i_{id}(pu) + v_{gd}(pu) \]  

(10)

The average active and reactive power fed into the grid is given by

\[ \begin{bmatrix} P_{ref} \\ Q_{ref} \end{bmatrix} = \begin{bmatrix} v_{id} & v_{iq} \end{bmatrix} \begin{bmatrix} i_{idref} \\ i_{iqref} \end{bmatrix} \]  

(11)

where

\[ P_{(pu)} = \frac{P_i}{S_{pu}^b} = \frac{P_i}{10^5} \]  

(12)

\[ Q_{(pu)} = \frac{Q_i}{S_{pu}^b} = \frac{Q_i}{10^5} \]

The reference currents can be found from equation (11) as
Development of control algorithm

The control topology for the system under study is shown in Figure 4. In this scheme, the current reference is computed by the power controller so as to attain the output power reference. For given reference power $P_{\text{ref}}$ and $Q_{\text{ref}}$, output reference current can be calculated by a power calculator\(^{22}\) as in equation (13). The control topology for a grid-connected inverter is shown in Figure 4.

The current control function is implemented by the ANFIS controller. However, for the purpose of assessment and evaluation, the conventional PI control is also implemented along with the proposed ANFIS controller. For a fair comparison, the gain setting for the PI control is obtained by PSO algorithm.

PSO

PSO technique based on swarm intellne is applied to acquire the coefficients of PI controller. PSO is an adaptable population-based optimization technique with inbuilt parallelism. It is not as much of to be lured on local optima unlike genetic algorithm. Number of methods to obtain the coefficients of PI controllers can be found in literature. The techniques like Ziegler–Nichols and internal model controller (IMC) are sluggish and reduce stability.\(^{23}\) The author has used PSO technique to get the optimized value of PI controller parameters. In Aravind and GirirajKumar,\(^{24}\) the PI control is applied to control the height of the fluid.

There are many advantages of PSO over the other heuristic optimization techniques. PSO is appraised as most robust and simple method. It is easy in implementation and not much sensitive to the type of objective function. The parameters required are only inertia weight and two acceleration coefficients. Furthermore, the solution is not much affected by the parameters and initial values. It can be summarized that PSO is capable to produce high-grade solutions in less time and steady convergence compared to other methods.

A swarm is made up of number of individuals called particles. The particles move in all directions in the search space and modify the position and velocity of the particle. The most excellent location is retained by the particle ever experiences. The path of each particle is oriented towards the best solution of the group (fitness) accomplished as yet. This position is known pbest. Along with this, each particle en routes for the finest previous position procured by any of the particle in its surroundings. That position is known as gbest. The whole lot of particles progresses in the search space and modifies its velocity. The equations of motion are given by

$$
\begin{align*}
\mathbf{v}(t+1) &= \mathbf{w}\mathbf{v}(t) + c_1(o(t) - x(t)) + c_2(nb(t) - x(t)) \quad (14) \\
x(t+1) &= x(t) + v(t+1) \quad (15)
\end{align*}
$$

where $o(t)$ is the old finest place of the particle and $nb(t)$ is the old finest position recognized by its neighbours.

The performance of the system is measured by its Absolute value of Error (ITAE) is being taken as the objective function. Here, Integral of Time multiplied by Absolute value of Error (ITAE) is being taken as the objective function. As the objective function is to be minimized, this method of optimization becomes an unconstrained one. The objective function ($J$) is given by

$$
J = \int_0^T |w(t)| dt \quad (16)
$$

The parameters selected for PSO are as per Table 1.

Table 1. Parameters selected for PSO.

| Item                        | Value |
|-----------------------------|-------|
| First inertia weight ($w_{\text{max}}$) | 0.9   |
| Final inertia weight ($w_{\text{min}}$) | 0.4   |
| Population volume           | 80    |
| Constants ($C_1$, $C_2$)    | 1.4, 1.4 |
| Maximum iteration number ($it_{\text{max}}$) | 100   |

The steps to implement PSO algorithm to get the optimum PI controller parameters are given in the following:

1. Give the initial value of the parameters such as population size, inertia weight and constants.
2. Initialize the particles with arbitrary position and velocity.
3. Compute the fitness value corresponding to all particles.
4. Find the local best and the global best.
5. Modify the position, velocity, local best and global best.
6. The steps from 3 to 5 are performed again and again till the maximum number of iterations are arrived at or the finest solution is found.

The structural outline to implement the PSO is given in Figure 5.
Design of ANFIS controller

The intelligent technique named as ANFIS having architecture of 2:6:9:9:1 is used and tuned using the hybrid learning algorithm. The ANFIS structure with two inputs, three membership functions and nine rules is shown in Figure 6.

A supervised learning algorithm following the Sugeno-type fuzzy system is used. The error between reference $d$ axis reference current $i_{d\text{ref}}$ and actual $d$ axis current $i_d$ ($e = i_{d\text{ref}} - i_d$) is applied to the input of the ANFIS controller. This error is also utilized to modify the precondition and consequent parameters. The purpose of the each layer is described as follows.

Layer 1: This layer can also be named as the fuzzification layer. Each square embodies a node. Error $(i_{d\text{ref}} - i_d)$ and change in error are the two inputs given to this layer, indicated by $x_1$ and $x_2$, respectively. Each input is allocated with three membership functions, which is represented through a square. Three gauss2mf membership functions are used and the related three nodes are given as

$$\mu_a(x) = \exp\left(\frac{-(x-c)^2}{2\sigma^2}\right)$$ (17)

where sigma ($\sigma$) is the width, $c$ is the centre of the membership function and $exp$ is the exponential function. Two stew parameters make up the gauss2mf function. The first function establishes the profile of the left-most curve specified by sig1 and c1. The second function establishes the profile of the right-most curve specified by sig2 and c2. The peak value of 1 is attained if $c1 < c2$. If not, the peak value is less than one.

The $S$ function is given by

$$\mu_a(x) = \begin{cases} 
&\text{sig1} = 0, &x \leq d \\
&\text{sig}1 = 2 \frac{(x-d)^2}{(e-d)^2}, &d < x \leq c \\
&\text{sig}2 = 1 - 2 \frac{(x-d)^2}{(e-d)^2}, &c < x \leq e \\
&\text{sig}2 = 1, &x > e
\end{cases}$$ (18)

where $c$ is the centre, $d$ is the left-hand breakpoint and $e$ is the right-hand breakpoint of the membership function.

Layer 2: The function of all the nodes of this layer is to multiply all the inputs and forward it to the next layer. It is represented by $\Pi$ inside a circle.

$$w_k = \mu_{ai}(x_1) \times \mu_{bi}(x_2)$$ (19)

where the value of $i = 1,2,3,4$ ... and $k = 1, 2, ..., 9$. The outcome of every node stands for the firing power.

Layer 3: In the third layer, all the nodes are embodied by a round shape. The normalized firing power is evaluated by this layer for each rule as given in the following

$$\frac{w_i}{w_1 + w_2 + w_3 + \cdots + w_9}$$ (20)

the value of $k$ varies from 1 to 9. The outcome of each node stands for the normalized weights.

Layer 4: In the fourth layer, all the nodes are embodied by a square. The function of each node is given as follows
\[ o_k = \overline{w_k} \cdot f_i = \overline{w_k} \cdot (p_i \cdot x_1 + q_i \cdot x_2 + r_i) \] (21)
the value of \( k \) varies from 1 to 9, \( i = 1, 2, 3, \overline{w_k} \) is the output of third layer and \( \{p_i,q_i,r_i\} \) indicates the parameter set. These parameters are named as consequent parameters.

Layer 5: It is the output layer and computes the output as follows
\[ Y = \sum_{k=1}^{q} \overline{w_k} f_k \] (22)
here, \( Y \) is the current used to regulate the \( d \)-axis current. Moreover, the same explanation is true for \( q \)-axis current controller.

Learning principle for ANFIS
The learning process modifies the parameters of the first and fourth layers. The hybrid learning principle is used to train these parameters. This principle is the synthesis of a gradient descent and least-square error (LSE) procedure. The parameters are identified as
\[ w_k = \mu_{a_i}^j(x_1) \cdot \mu_{a_j}^j(x_2) \times \cdots \times \mu_{a_n}^j(x_n) \] (23)
where \( j \in (1,2,\ldots,MFn_j) \) and \( j = 1,2,\ldots,MFn_1, MFn_2,\ldots, MFn_n \) are the membership functions for the \( n \) inputs; \( \mu_{a_i}^j \) is the \( \text{ith} \) membership function, \( w_k \) is the firing strength of the \( k \)-th rule and \( MFn_j \) is the number of membership function for the \( j \)-th input given as
\[ f_k = \sum_{j=1}^{n} a_j x_j + b_j \] (24)
The value of \( i \) varies from 1 to \( R \) and \( R \) is the total number of rules. The linear parameters are \( a_j \) and \( b_j \) of the \( i \)-th rule. The output of the system is given as
\[ y = \sum_{i=1}^{R} w_i f_i \] (25)
The objective function is specified as the following
\[ e(k) = Y_d(k) - Y(k) \] (26)
where \( Y_d(k) \) is the desired output and \( Y(k) \) is the controller output.

The input in the form of a vector is given by
\[ \hat{X}(k) = [x_1(k), x_2(k), x_3(k), \ldots, x_n(k)]^T \] (27)
The weights are represented by
\[ A = \begin{bmatrix} a_1^1 & a_1^2 & a_1^3 & \cdots & a_1^n \\ a_2^1 & a_2^2 & a_2^3 & \cdots & a_2^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_n^1 & a_n^2 & a_n^3 & \cdots & a_n^n \end{bmatrix} \] (28)
The output in the form of a vector is given by
\[ Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_n \end{bmatrix} \] (29)
This is \((n \times 1)\) matrix. The output may be given by
\[ A = A\hat{X} \] (30)
The squared error \( A\hat{X} - Y^2 \) in equation (28) is reduced to minimum when \( \hat{X} = \hat{X}^* \), which is called the LSE. It should satisfy the normal equation
\[ \hat{X}^* = (A^T A)^{-1} A Y \] (31)
\( A^T \) is the transpose of the matrix \( A \). \((A^T A)^{-1}\) is the pseudo-inverse of \( A \) (for \( A^T \) is a non-singular matrix.)
Following assumptions have been made:
1. The stated feed-forward adaptive network has \( L \) layers.
2. The \( k \)-th layer has \( N(k) \) nodes.
3. The output of node \( n \) can be given as
\[ Y_{k,n} = f_k, n(Y_{k-1,1}, \ldots, Y_{k-1,N(k-1)}, a, b, c, \ldots) \] (32)
where \( Y_{k,n} \) is the output in the \( k \)-th layer and \( a, b \) and \( c \) are the parameters of the \( k \)-th node.
The sum of the square of the error for the \( p \)-th term \((1 \leq p \leq P)\) entry of the training data set is given as
\[ E_p = \sum_{i=1}^{N(L)} (d_i - Y_{L,i})^2 \] (33)
Here, it is assumed that the training data set has \( P \) entries, \( d_i \) is the \( i \)-th component of the \( p \)-th output vector and \( Y_{L,i} \) is the \( i \)-th component of the real output vector.
The overall error is given by
\[ E = \sum_{p=1}^{P} E_p \]
This error \( E \) should be reduced to minimum.
To realize the gradient descent, first the error rate is calculated and for the \( i \)-th output node at layer \( l \) is given by
\[ e_{l,k} = \frac{\partial E_p}{\partial Y_{l,k}} \] (34)
where \( e_{l,k} = -2(d_k - Y_{l,k}) \).
The error for the internal node at the \( i \)-th point of layer \( l \) is evaluated iteratively as
\[ \frac{\partial E_p}{\partial Y_{l,k}} = \sum_{q=1}^{N(l+1)} \frac{\partial E_p}{\partial Y_{l+1,k}} \frac{\partial f_{l+1,q}}{\partial Y_{l,k}} \] (35)
and
\[
\frac{\partial E_P}{\partial \alpha} = \frac{\partial E_P}{\partial Y_{l,k}} \frac{\partial Y_{l,k}}{\partial \alpha} = e_{l,k} \frac{\partial h_{l,k}}{\partial \alpha} \tag{36}
\]
where \(\alpha\) is the parameter of the \(k\)th node at layer \(l\).

The derivative of \(E\) relating \(\alpha\) is given as
\[
\frac{\partial E_P}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E_P}{\partial \alpha} \tag{37}
\]

The parameter \(\alpha\) is updated by
\[
\Delta \alpha = -\delta \frac{\partial E_P}{\partial \alpha} \tag{38}
\]
where \(\delta\) is the learning rate. The updated value of \(\alpha\) can be written as
\[
\alpha_{\text{new}} = \alpha_{\text{old}} + \Delta \alpha = \alpha_{\text{old}} - \delta \frac{\partial E_P}{\partial \alpha} \tag{39}
\]

Once all the training data have been processed, only then the update occurs. The total set of parameters is considered as \(C\) and \(C1\) as the premise set and \(C2\) as the consequent set. The hybrid learning technique involves both forward pass and backward pass to built entire training data set. The forward pass keeps the parameter set \(C1\) unaffected, but \(C2\) is modified using the LSE, and the output is evaluated layer by layer. This development goes on until the correlated row of matrix \(A\) and \(Y\) of equation (30) is attained. The same continues till the matrix is complete. Once the matrix is obtained, consequent parameter set \(C2\) is calculated using equation (31). Equations (35) and (36) compute the error and the derivative of error corresponding to each node. The backward pass processes these error signals from the output end to the input end. It results out the gradient vector corresponding to each training data. Finally, the input parameters are modified as per equation (39).

**MATLAB simulation results**

MATLAB/Simulink model of the system is made and the performance is tested under nominal parameters and with parametric uncertainties. A three-phase VSI, an RL-type filter and a star-connected transformer, is used to feed the energy into the grid from renewable energy source with a power of 67 kW into the three-phase grid. The grid line voltage is 10 kV with a frequency of 60 Hz. A direct current (DC) voltage source of 500 V is applied to the input of VSI. The system is simulated with PI control as well as proposed ANFIS based control for evaluation and comparison purpose.

**Case A: Operation without parametric uncertainties**

The parameters of the system under study are given in Table 2. \(R_1\) and \(L_1\) represent the primary side resistance and inductance of the transformer, respectively. \(R_2\) and \(L_2\) represent the secondary side resistance and inductance of the transformer, respectively. \(R_m\) and \(L_m\) represent the magnetizing branch parameters of the transformer. The \(R_f\) and \(L_f\) are the resistance and inductance of the line filter, respectively.

The performance of the grid-interfaced inverter with PI control is shown in Figures 7–11. The results of grid-interfaced inverter with ANFIS control are demonstrated in Figures 12–16.

**Table 2. System parameters in case A.**

| Module                  | Parameter and value                      |
|-------------------------|------------------------------------------|
| Transformer             | 67 KVA, 250 V/10 kV, 60 Hz, Y-Y          |
| Per-phase parameters    |                                          |
| of the transformer      |                                          |
| \(R_1\)                 | 0.62 mΩ                                   |
| \(L_1\)                 | 49.736 µH                                  |
| \(R_2\)                 | 1.1 Ω                                     |
| \(L_2\)                 | 79.577 mH                                  |
| \(R_m\)                 | 5.105 Ω                                   |
| \(L_m\)                 | 1326.29 H                                 |
| L-type filter           |                                          |
| Grid voltage (line-to-line) | 500 V                                      |
| Fundamental frequency   | 60 Hz                                     |
| DC link voltage \(V_{dc}\) | 80 kV, 0.8 lag pf                         |

**Case B: Operation within parametric uncertainties**

The parameters \(R_f\) and \(L_f\) are chosen smaller values as compared to case A. The parameters used are shown in Table 3. The results of the grid-interfaced system with PI control are demonstrated in Figures 17–19 and with ANFIS-based control is shown in Figures 20–22.

It is observed from the results that the fluctuations and ripples in the output powers are increased as compared to case A with both of the controllers. But the fluctuations are very large with PI control as compared to ANFIS control. The response time of ANFIS control is much better than PI control. Both the grid current total harmonic distortion (THD) and inverter-injected current THD are increased to 7.48% and 9.18%, respectively, with PI control. Here, ANFIS-based control illustrates enhanced performance in terms of inverter-injected current quality. Implementation of ANFIS control limits these values to 3.14% and 2.12%, respectively.

The response of ANFIS control is very fast as compared to PI control, which is evident from Figures 7 and 12. The grid current and inverter-injected current THD are 2.26% and 2.55%, respectively, with PI control. However, using ANFIS-based control, the respective values of THD are 2.18% and 2.11%. The Figures 9, 10, 14 and 15 demonstrate the bidirectional power flow of the system. In the beginning, the current fed by the inverter is higher than the load connected, so grid absorbs the excess current as depicted from the negative grid power and phase difference of 180° between
the voltage and current. At \( t = 1 \) s, the load demand is increased and the grid feeds the scarce amount load current as evident from positive grid power and phase relationship of \( 0^\circ \) between grid voltage and current.

The result shows that both of the control methods, PI control and ANFIS control, have capability of bidirectional power flow and to regulate the powers to the reference values. However, the PI control has slow response and more ripples in the active and reactive power. Whereas, the ANFIS-based control has less ripples in the active and reactive power at steady state along with fast response. The grid current and inverter-injected current THD is 2.26\% and 2.55\%, respectively, with PI control. However, using ANFIS-based control, the respective values of THD are 2.18\% and 2.11\%.
The conventional PI controller results into the substantial fluctuations and slow response. Due to parameter uncertainties, the output power ripples have increased as compared to case A. However, the ANFIS control has very less output power ripples. At the same time, it demonstrates fast response with fewer fluctuations. The grid current THD is 7.48% with PI control, whereas it is 3.34% with ANFIS control. The THD of the current injected by the inverter is 9.18% with PI control, whereas it is 2.12% with ANFIS control.
Figure 15. The active and reactive powers illustrating bidirectional power flow with ANFIS control in case A.

Figure 16. The phase A voltage and current illustrating bidirectional power flow with ANFIS control in case A.

Figure 17. The active and reactive powers with PI control in case B.
Therefore, power quality of the current injected by the inverter is enhanced significantly with ANFIS-based control even under the parametric uncertainties.

**Conclusion**

The main objective of grid-interfaced inverters is to inject high-quality active and reactive power with sinusoidal current. A large number of control techniques for three-phase grid-interfaced inverters can be found in the literature for the interfacing inverters, but their adaptability to dynamic systems is very poor. The operation under parametric uncertainties has not been given much consideration in this work. This work presented a novel adaptive network–based fuzzy inference control algorithm for the grid-connected inverter in order to control the power injection into the grid. The main purpose is to improve the response time, reduce the steady-state oscillation in the output powers and enhance the power quality. For assessment and evaluation reason, the conventional PI control is also simulated as current regulator. As the variation in the parameters of filter and transformer may affect the performance of the system, both PI- and ANFIS-based controllers are also simulated under the parametric uncertainties. However, the ANFIS-based control shows superiority in comparison to conventional PI control in terms of fast response, decreased steady-state fluctuations, better power quality and increased robustness.

In contrast with the PI control, the proposed ANFIS-based control has remarkable improvement in the response speed, oscillations in output powers and power quality of injected current from the inverter. In addition to this, ANFIS-based control is much robust against parametric uncertainties.

**Table 3.** System parameters in case B.

| Module                          | Parameter and value                                                                 |
|---------------------------------|--------------------------------------------------------------------------------------|
| Per-phase parameters of the transformer | $R_1 = 437.5 \, \mu\Omega, L_1 = 34.185 \, \mu\text{H}$, $R_2 = 0.7 \, \Omega, L_2 = 55.7039 \, \text{mH}$, $R_m = 5 \times 10^5 \, \Omega, L_m = 1326.29 \, \text{H}$ |
| L-type filter                   | $R_f = 1.4 \, \text{m}\Omega, L_f = 175 \, \mu\text{H}$                           |

**Figure 18.** The frequency spectrum of grid current with PI control in case B.

**Figure 19.** The frequency spectrum of inverter current with PI control in case B.

**Figure 20.** The active and reactive powers with ANFIS control in case B.
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