A Quasi-Resonant Buck Converter experiences a high degree of non-linearity in its control characteristics mainly due to switching action or fluctuations in system parameters and to achieve the desired regulation irrespective of line and load disturbances feedback control is indispensably required. A common feature of control methodology is that the algorithm is analytically described by equations such as algebraic, difference, differential and so on and the synthesis of such algorithm requires a mathematical model. Hence, it is the responsibility of an engineer to determine how to accurately describe a system mathematically and how to formulate proper assumptions and approximations so that the system shall be realistically characterized by a mathematical model. If the assumptions pertaining to the mathematical model are satisfied, many of the model-based control techniques such as Bode or Nyquist plot provide good stability, robustness to model uncertainties and disturbances, and speed of response. In real-life applications or in a complex process such as cement plant, nuclear reactor and the like requires complicated mathematical analysis, floating point algorithm and complex branching which makes the implementation of mathematical model very tedious and time consuming.

A linear controller is probable to be unstable if the required range of operation is high because the non-linearities in the system cannot be properly compensated. In addition, if the model is ill-defined or if the model has parameters whose value is partially identified, the algorithm based on such incomplete information will not give satisfactory results and the linear
controller exhibits degradation in its performance or instability. This reality, inevitably promotes the endeavour to control methods that will more or less incorporate the non-linear dynamics into the design. A non-linear controller handles the nonlinearities in large range of operation and such nonlinearities shall be intentionally introduced into the controller part of a control system so that the model uncertainties may be tolerated. Advancement in computer technology made the implementation of non-linear control methodologies such as adaptive control (Gopal 2009), sliding mode control (Ahmed et al 2003), (Lai et al 2005), current programmed control (Jingquan Chen et al 2003), (Erickson and Maksimovic 2006), intelligent control such as Fuzzy and Neuro-Fuzzy control, etc., a relatively simple task.

4.1 PI CONTROL

A PI or Proportional-Integral controller is a linear controller which fuses the properties of both P and I controller and the algorithm provides a balance of complexity and capability in order to be widely used in industrial applications pertaining to process control. The proportional value determines the reaction to the recent error whereas the integral value determines the reaction based on sum of recent error and the weighted sum of two actions is used to adjust the process through a control element.

The Equation (4.1) that describes the nature of P controller is

\[ u(t) = K_P e(t) \]  

(4.1)

where \( K_P \) is the proportional gain, \( e(t) \) is the error and \( u(t) \) is the perturbation in output signal of controller from the base value corresponding to normal operating conditions; the base value is adjusted to produce zero error under the condition of no disturbance and changes in set-point. It with no integration property always exhibit steady-state error in the presence of disturbances and changes in set-point. The error, of course, must be made negligibly small by
increasing the gain of proportional controller; however, as the proportional gain is increased, the closed-loop performance of the system shows a relatively maximum overshoot and long settling time. To remove steady-state offset in controlled variable of a process, an extra intelligence is added to the P controller and it is called the integral action which induces robust voltage regulation at output against parameters uncertainties and external disturbances (Ramirez et al, 2001), (Zafiriou and Morari 1989). The controller is a PI controller whose mathematical notation is depicted in Equation (4.2).

\[
    u(t) = K_p e(t) + \frac{1}{K_i} \int_0^t e(t) \, dt
\]

where \( K_i \) is the integral or reset time. A linear PI controller has thus two tuning parameters namely \( K_p \) and \( K_i \); the integral action (Gopal 2009) in this controller removes steady-state offset in the controlled variable of a process.

4.2 INTELLIGENT CONTROL

It is necessary to increase sophistication of the controller to handle the complexity of non-linearities such as backlash, coulomb friction, dead zone or saturation in the system and in order to extend the operating range of the controller to wide variations in either line or load, (Criceono et al 2001) it is more appropriate to use a methodology from Artificial Intelligence so as to achieve intelligent control action. Intelligent control such as Fuzzy or multi-valued logic was propounded by Dr. L.A. Zadeh, Professor, University of California, Berkley, California 94720 (Bose 1994), (Hua Li and Madan Gupta 1995), (Buckley 2011), (Yen and Langari 1999), (Zimmerman 2011) and is largely rule-based because the dependency involved in its deployment is too complex to permit an analytical representation. To deal with such dependency, the mathematics of fuzzy system integrates the experience and knowledge gained in the operation of a similar plant into control algorithm
and is of great value for problems where mathematical model of system is difficult to be obtained due to complexity, non-linearity and imprecision (Perry et al 2005), (Feng et al 2002); however, the expense lies in high computational density (Weidong Xiao and Dunford 2004). The algorithm consists of a set of IF-THEN rules (Fumio Ueno et al 1991), (Mendel 1995) and is based on expert’s knowledge and is normally of the form:

\[
{\text{IF}} \ (\text{process state}) \ {\text{THEN}} \ (\text{control action}) \ {\text{or otherwise}}
\]

\[
{\text{IF}} \ (\text{a set of conditions are satisfied}) \ {\text{THEN}} \ (\text{a set of consequences can be inferred})
\]

The process state part of rule is called the antecedent part and it contains a description of the process state at the \(k^{th}\) sampling instant whereas the control action part of the rule is the consequent part (Berenji and Khedkar 1992) and it contains a description of the control variable produced as per the particular process state. The collection of such fuzzy rules which are expressed as conditional statements forms the rule base. There is no procedure for deciding the optimal number of fuzzy rules since a number of factors is involved in the decision such as performance of the controller, efficiency of computation, human operator’s behavior, and the choice of linguistic variables. In practice, it is important to ensure the consistency of fuzzy rules in order to minimize the possibility of contradiction. For instance, in the case of two-input-single-output fuzzy system, the fuzzy control rule is of the form:

\[
R_1: \text{ IF } x \text{ is } A_1 \text{ AND } y \text{ is } B_1 \text{ THEN } z \text{ is } C_1
\]

\[
R_2: \text{ IF } x \text{ is } A_2 \text{ AND } y \text{ is } B_2 \text{ THEN } z \text{ is } C_2
\]

\[
R_3: \text{ IF } x \text{ is } A_3 \text{ AND } y \text{ is } B_3 \text{ THEN } z \text{ is } C_3
\]

\[
R_4: \text{ IF } x \text{ is } A_4 \text{ AND } y \text{ is } B_4 \text{ THEN } z \text{ is } C_4
\]
and so on; this fuzzy rule-set may be combined as one single rule by means of an union operator and shall be expressed as \( R = R_1 \cup R_2 \cup \ldots \cup R_N \) in which the fuzzy relation \( R \) is regarded as a fuzzy relation whose function is to map elements from one universe, say \( U \), to another universe, say \( V \) through the Cartesian product of two universes and its membership function is depicted in Equation (4.3) (Fang Hsien Wang and Lee 1995) as

\[
\mu_R(x,y) = \mu_{AXB}(x,y) = \min\{\mu_A(x,y), \mu_B(x,y)\}; \quad x \in U, y \in V \quad (4.3)
\]

Here, \( x, y \) and \( z \) are the linguistic variables (Zadeh 1973) representing two process state variables and one control variable respectively in natural language; the proper choice of variables is essential to the characterization of the operation of a fuzzy system. The variables \( A_1, B_1 \) and \( C_1 \) are the linguistic values of the linguistic variables \( x, y \) and \( z \) in the Universe of discourse \( U, V \) and \( W \) respectively. A Fuzzy Controller (Drainkov et al 1997) incorporates attractive features such as good performance and simplicity and it does not require small signal model of the converter and is easier to implement (Smyej and Cheriti 1999); the performance of such controller depends on rule size and tuning parameters (Sung-Hoe Huh and Gwi-Tae Park 1999). In addition, the control algorithm is generalized and hence same control rules may be applied to various DC-DC converters with minor modifications depending upon the topology of the converter and parameters (Arulselvi et al 2006). It is highly adaptive in nature (Lin and Hua 1993) and can also exhibit increased reliability, robustness in the face of changing parameters, saturation effects and external disturbances and so on. It extends the control capability even to those operating conditions such as large signal dynamics and parameter variations where linear controller fail (Corcau et al 2010); fundamentally, there are two fuzzy models namely T.Takagi-M.Sugeno model (Takagi and Sugeno 1985) and E.H.Mamdani model in which the former model possess an excellent capability in complex and uncertain system description and is suitable for modeling the nonlinear system by fuzzy local models combined using an inference mechanism.
corresponding to various operating points (Yu and Sun 2001); it has found applications in control, prediction and inference (Jang 1993) such as information retrieval, decision-making, database management, signal processing and so on (Jang and Sun 1995).

Figure 4.1 clearly depicts the basic configuration of E.H.Mamdani’s Fuzzy controller (Idiarie et al 2004) whereas Figure 4.2 illustrates the architecture of a Fuzzy control system (Abdelnour, 1991). It consists of four components (Chuen-Chien Lee 1990), (Corcau and Constantinache 2007), (Nik Ismail et al 2010) namely a fuzzifier, a knowledge base containing rule and data base (Melin and Vidolov 2003), a decision-making logic and a defuzzifier; in brief, fuzzifier and de-fuzzifier are used to communicate with the real world; a defined set of rules is used for governing the converter in order to obtain the desired performance at the output and the inference engine is responsible for making fuzzy decisions based on the given input and a set of rules (Ramos et al 2000); the operation of Fuzzy controller does not rely on how accurate the mathematical model is, however on how effective the rules are or otherwise, the operation of Fuzzy controller is based on expert’s knowledge of the plant instead of a precise mathematical model (Passino and Yurkovich 1997). It thus generated a good deal of interest in applications relating to power electronics and electrical drive systems due to its capability of fast computation with high precision.

![Figure 4.1 Basic configuration of E.H.Mamdani’s Fuzzy controller](image_url)
Figure 4.2 Architecture of Fuzzy control system
In spite of the usefulness of Fuzzy control, standard method doesn’t exist for transforming human knowledge into the rule base and database of a fuzzy inference system; in addition, stability analysis of a fuzzy system is not easy and parameter tuning is generally a time-consuming procedure due to the non-linear and multi-parametric nature of fuzzy systems (Ho Jae Lee et al 2001). Hence, the neural network which has a large number of interconnected processing nodes to demonstrate the ability to learn and generalize from training data and which has many successful applications such as T.Sejnowski and C.Rosenberg’s NETtalk for text- to speech conversion; K.Fukushima, S.Miyaka and T.Ito’s Neocognitron’s for visually recognizing hand-written Arabic numbers (Fukushima et al 1983); S.Grossberg’s vision processing network to synthesize coherently three-dimensional form, color and brightness perception; A.G.Barto, R.S.Sutton and C.W.Anderson’s control of cart-pole problem (Barto et al 1983); C.W.Anderson’s control of an inverted pendulum and F.C.Chen’s non-linear self-tuning adaptive control (Chen 1989) is integrated with fuzzy logic in order to provide a promising methodology known as Neuro-Fuzzy Inference System.

A Neuro-Fuzzy Inference System is a multi-layered connectionist network (Lin and George Lee 1991) which combines parallel computation and learning abilities of neural networks (Tang et al 2011), (Narendra and Annasamy 1989) with the human-like knowledge representation and explanation ability of fuzzy logic control and decision systems (Cheng-Jian Lin et al 2008) and the structure of such system has input terminals, hidden layers to represent membership functions and fuzzy rules and an output layer. It is isomorphic to fuzzy logic control systems in terms of their functions and is also referred to as universal approximators (Wang and George Lee 2002). In general, there are three types of neural-fuzzy networks (Nauck et al 1997) existing and are named as Co-operative Neuro-Fuzzy system (Kosko 1992), Concurrent Neuro-Fuzzy system and Hybrid Neuro-Fuzzy system. A Hybrid
Neuro-fuzzy system shall be developed in different ways with each researcher has defined their own architecture and most particularly are FALCON or Fuzzy Adaptive Learning Control Network, ANFIS or Adaptive-Network based Fuzzy Inference System (Abdul Ofoli and Ahamed Rubaai 2004), (Jang et al 1997), (Principe et al 2000), GARIC or Generalized Approximate Reasoning based Intelligence Control, NEFCON or Neuronal Fuzzy Controller; ANFIS is an adaptive network in advance of the different kinds of feed-forward neural network with supervised learning capability; it is applied in applications such as non-linear function modelling (Jang 1991,1993), time series prediction (Jones et al 1990, Jang 1993, Jang and Sun 1993), on-line parameter identification for control systems (Jang 1993) and design of Fuzzy controller (Jang 1992). Networks similar to such adaptive network were also proposed independently by C.T. Lin and C.S.G.Lee (Lin and George Lee 1991), (Lin and George Lee 1996) and L.X.Wang and J.M.Mendel (Wang and Mendel 1992). However, a major drawback is that there is much freedom in the choice of structural implementation and it is difficult to decide how complex a structure is necessary for the desired control to achieve better system performance (Abdul Ofoli and Ahamed Rubaai 2004).

4.2.1 Architecture of ANFIS

It is assumed that the fuzzy inference system under consideration has two inputs x and y and an output z for which Type: 3 T.Takagi and M.Sugeno’s fuzzy rules are used. For a first-order M.Sugeno’s model (Yager and Filev 2002), a typical rule base with two fuzzy rules is expressed as:

Rule 1: IF x is $A_1$ and y is $B_1$ THEN $f_1 = p_1x + q_1y + r_1$
Rule 2: IF x is $A_2$ and y is $B_2$ THEN $f_2 = p_2x + q_2y + r_2$
Rule 3: IF x is $A_3$ and y is $B_3$ THEN $f_3 = p_3x + q_3y + r_3$
Rule 4: IF x is $A_4$ and y is $B_4$ THEN $f_4 = p_4x + q_4y + r_4$
The Takagi-Sugeno fuzzy model has the main advantage to model a system accurately; either globally or locally (Quah and Quek 2006). The accurate global learning ability motivates the practical applications of this model in non-linear system estimation (Yen and Langari 1999); the local learning ability provides a course of interpretability of the local models in the localized subspaces (Johnson and Babuska 2003, Johnson et al 2000, Yen et al 1998). Figure 4.3 illustrates a two-input first-order M.Sugeno’s fuzzy model with two IF-THEN rules and Figure 4.4 clearly depicts the equivalent architecture of such ANFIS.

\[ f_i = \omega_i x + \omega_{2i} y + \tau_i \]

\[ \hat{f}_i = \frac{\omega_1 \hat{f}_1 + \omega_2 \hat{f}_2}{\omega_1 + \omega_2} = \omega_{i1} + \omega_{i2} \]

\[ \tilde{f}_i = \omega_i x + \omega_{2i} y + \tau_i \]

**Figure 4.3** A two-input first-order M.Sugeno’s Fuzzy model with two rules
Figure 4.4 ANFIS architecture

where nodes have the similar function; Layer1 is the input linguistic layer, Layer2 is conjunction layer, Layer3 is normalization layer, Layer4 is rule or functional layer and Layer5 is summation layer. It is noted that the structure of this adaptive network is not unique and hence layers 3 and 4 shall be combined to obtain an equivalent network with only four layers. An advantage is that it uses a hybrid learning procedure for estimation of the premise and consequent parameters (Tahmasebi and Hezarkhani 2010).