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# An Interval Type-II Robust Fuzzy Logic Controller for a Static Compensator in a Multimachine Power System

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**Abstract**—This paper presents a novel fuzzy logic based controller for a Static Compensator (STATCOM) connected to a power system. Type-II fuzzy systems are selected that enable the controller to deal with design uncertainties and the noise associated with the measurements in the power system. Interval type-II fuzzy is computationally more effective than the ordinary type-II fuzzy systems and is more suitable for the power network with fast changing dynamics. Using a proportional-integrator approach the proposed controller is capable of dealing with actual rather than deviation signals. The STATCOM is connected to a multimachine power system in order to provide extra voltage support and improve the system dynamic performance. Simulation results are provided to show that the proposed controller outperforms a conventional PI controller during large scale faults as well as small disturbances. The type-II fuzzy membership functions provide a robust performance for the controller and eliminate the need for a model based adaptive control scheme.

## I. INTRODUCTION

STATIC Compensators (STATCOM) are power electronics based shunt *Flexible AC Transmission System* (FACTS) devices which can control the line voltage at the point of connection to the electric power network. Regulating the reactive and active power injected by this device into the network provides control over the power flows in the line and the DC link voltage inside the STATCOM respectively [1]. A power system containing generators and FACTS devices is a nonlinear system. It is also a non-stationary system since the power network configuration changes continuously as lines and loads are switched on and off.

In recent years most of the papers have suggested methods for designing STATCOM controllers using linear control techniques, in which the system equations are linearized at a specific operating point. Based on the linearized model, the PI controllers are fine tuned in order to have the best possible performance [2]-[5]. The drawback of

such PI controllers is that their performance degrades as the system operating conditions change. Linearizing the nonlinear system in the vicinity of the operating condition cannot be a practical solution because of the ever-changing nature of the power network, either due to faults and disturbances or the normal changes in the operating conditions. Moreover, the process of fine tuning a PI controller in such a highly nonlinear environment is a complex and challenging task.

Traditional nonlinear adaptive controllers on the other hand can give good control capability over a wide range of operating conditions [6]-[9], but they have a more sophisticated structure and are more difficult to implement compared to linear controllers. In addition, they need a mathematical model of the system to be controlled, which in most of the cases cannot be obtained easily.

Intelligent controllers on the other hand have the potential to overcome the above mentioned problems. Fuzzy logic based controllers have, for example, been used for controlling a STATCOM [10],[11]. Essentially, a fuzzy controller performs like a nonlinear gain scheduling controller. However, in the traditional fuzzy approach the parameters of the fuzzy membership functions are fixed. The performance of such controllers can further be improved by adaptively updating their parameters. Mohagheghi *et al.* [13] applied the *Controller Output Error Method* introduced by Anderson *et al.* [12] in order to implement an adaptive fuzzy controller for the STATCOM.

Adaptive controllers can efficiently deal with the uncertainties associated with the power system. These uncertainties can be in terms of modeling imperfection, noisy sensor measurements and/or unexpected disturbances in the system. However, the improved performance of the adaptive techniques comes at the price of higher computational complexities. This is due to the fact these controllers need a model of the plant to be controlled that can estimate the plant outputs. The controller parameters are then adjusted using these estimates [25]. Deriving a mathematical model of the plant to be controlled is often not a simple task and for a variety of complicated systems such as a multimachine power network can be impractical. An alternative solution can be estimating a model of the plant using intelligent techniques such as neural networks [26]. The authors have implemented this scheme for a neural network based controller for a STATCOM in a power system [27]. The same approach can be employed for designing adaptive fuzzy controllers, where the membership

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functions of the fuzzy controller for the input and/or output variables are adjusted based on the estimated state of the power system at one step ahead. These estimates come from a neural network based identifier (neuroidentifier) that undergoes continuous online training in order to track and estimate the plant dynamics [27]. Clearly, implementing such an online trained neuroidentifier requires additional computations. However, for cases where the computational complexity is of main importance or an adaptively changing fuzzy controller structure is for any reason not desired, measures have to be taken in order to enable the controller with its fixed structure to deal with system uncertainties.

This can be achieved by introducing another measure of uncertainty to the membership functions and membership grades of the fuzzy controller. This is referred to as type-II fuzzy logic [17]. In this approach, the fuzzy sets have blurred boundaries (uncertainties within uncertainty); therefore, the membership grade of a specific sensor reading in a certain fuzzy set is not a crisp number anymore. Instead, it is a fuzzy set itself. This can help the controller reduce the effect of the system uncertainties, no matter what the source is (external disturbance, model error or measurement noise).

An interval type-II fuzzy controller is design in this paper that can perform as a robust nonlinear controller for a STATCOM connected to a multimachine power system. Detailed procedure for designing the controller is presented in the next sections. The performance of the controller is also compared with the traditional PI controller during large scale and small scale disturbances.

## II. TYPE-II FUZZY LOGIC SYSTEMS

Type-II fuzzy sets were introduced by Zadeh as an extension to the concept of fuzzy sets [14]. The membership grade of a type-II fuzzy set is a fuzzy itself [16]. This fuzziness in the degree of membership can represent an important fact that underlines the basis of fuzzy systems: the fuzzy sets/rules/consequents are not certain, instead they are derived based on the experience of the human expert. Therefore the increased fuzziness introduced by type-II fuzzy sets can enable the fuzzy system to handle the inexact information in a logically correct matter [15]. But perhaps the most important aspect of type-II fuzzy in a real world problem such as power systems analysis/control is that it can help the fuzzy system deal with the noisy measurements more efficiently.

Figure 1.a shows a typical type-I ordinary fuzzy membership function (MF). As it can be seen, there is a crisp number as the membership grade associated with each crisp input  $x$ . A type-II fuzzy membership function can be derived from this by blurring the boundaries of the main MF (Fig. 1.b). This can be interpreted as the fuzziness in the membership grade and the fact that for each input  $x$  there can be more than one possibility of membership grade. In other words, for each input  $x$  there is an ordinary type-I fuzzy set  $A$ , referred to as the *secondary membership function*, associated with it, which defines different values of the membership grade and their possibilities [17].

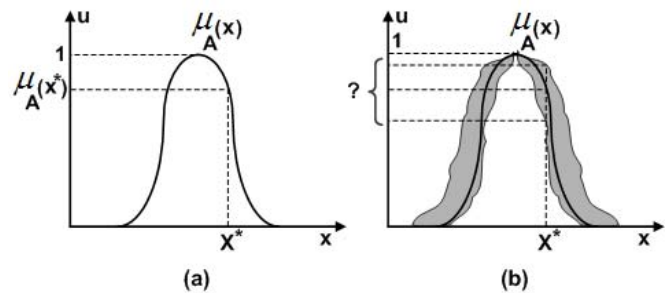


Fig. 1. Typical fuzzy membership functions: (a) type-I, (b) type-II.

If for the type-II fuzzy set  $\tilde{A}$ , the membership grade of the input variable  $x$  varies between  $u_1$  and  $u_2$  with a type-I fuzzy set of  $\mu_A(u)$ , then the membership grade of  $x$  can be expressed as<sup>1</sup>:

$$\mu_{\tilde{A}}(x, u) = \int_{u \in [u_1, u_2]} \mu_A(u) / u \quad (1)$$

Therefore, the type-II fuzzy set can be simplified as the summation of the membership grades of all  $x$ :

$$\tilde{A} = \int_{x \in X} \int_{u \in U} \mu_{\tilde{A}}(x, u) / (x, u) \quad (2)$$

General type-II fuzzy systems are computationally intensive. The problem can be considerably simplified if the secondary MFs are interval sets<sup>2</sup>. Such systems are referred to as interval type-II fuzzy sets, in which the secondary MFs are either zero or one [18]. A simplified case of (2) exists when the interval type-II sets are considered. For such a system:

$$\mu_A(u) = \begin{cases} 1 & u \in U \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Interval type-II fuzzy systems are considered in this paper and their basic design procedure is explained in the next sections. For the more general case, the reader is referred to [17].

## III. INTERVAL TYPE-II FUZZY LOGIC SYSTEMS

Figure 2 shows the schematic diagram of an interval type-II fuzzy logic controller. Basic equations and the main differences between type-I and type-II fuzzy systems are discussed in this section. More elaborate explanations on type-II fuzzy can be found in [17]-[20]. Also, Lee [21] presents a detailed discussion of type-I (ordinary) fuzzy systems.

### A. Fuzzification

Fuzzy systems are essentially nonlinear mappings from a set of crisp inputs to a set of crisp outputs, through a set of fuzzy variables. The first stage in this process is transforming the crisp input to a type-II fuzzy variable. Various standard or non-standard fuzzifiers can be employed for this matter. The only challenge here lies in the definition of membership grade fuzziness. Clearly, the primary and

<sup>1</sup> The symbol “/” should not be confused with the algebraic division. In fuzzy literature this is a common way of relating any crisp variable  $u$  to its corresponding membership function.

<sup>2</sup> An interval set is a set that includes either 0 or 1.

secondary MFs should be formulated in a way that reduces the problem complexity as much as possible. The common approach is to define a lower MF and an upper MF for each type-II MF. These are both type-I fuzzy sets. The bounded region between the lower and the upper MFs is called the *footprint of uncertainty* of a type-II MF [17]. Therefore, equation (1) for the  $k^{\text{th}}$  MF of the type-II fuzzy system can now be rewritten as:

$$\mu_{\tilde{A}_k}(x, u) = \int 1/u \quad u \in [\underline{\mu}_{A_k}(x), \bar{\mu}_{A_k}(x)] \quad (4)$$

where:

$\underline{\mu}_{A_k}(x)$ : lower MF for the  $k^{\text{th}}$  type-II MF,

$\bar{\mu}_{A_k}(x)$ : upper MF for the  $k^{\text{th}}$  type-II MF.

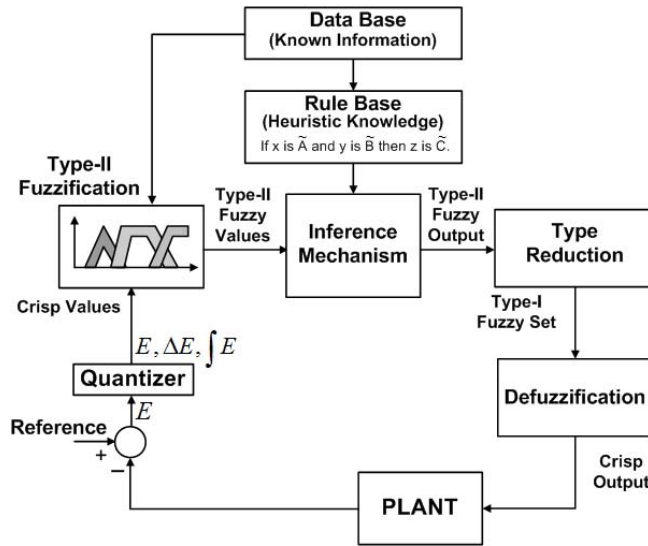


Fig. 2. Schematic diagram of interval type-II fuzzy logic controller.

Various techniques exist for defining the lower and upper MFs depending on the membership function and the type of uncertainty [18]. For the special case of Gaussian functions considered in this study, the lower and upper MFs are considered to have the same center, but different standard deviations (Fig. 3).

### B. Rule Base

Any fuzzy system includes a set of conditional statements (in the form of *Modus Ponens*) known as the fuzzy rule base. The fuzzy rule base can be derived from the data base (expert knowledge/operator experience), mathematical models or a combination of both. It can also be fixed (robust mode) or adaptive (learning mode). In general, in a multi input single output fuzzy system:

Rule  $j$ :

$$\text{If } x_1 \text{ is } F_1^j, \dots, \text{ and If } x_n \text{ is } F_n^j, \text{ Then } y \text{ is } G^j(x_1, \dots, x_n). \quad (5)$$

where depending on the inference mechanism used the function  $G^j$  can be a polynomial, a constant or a single value. In fuzzy logic, the Modus Ponens rules are extended to *Generalized Modus Ponens* (GMP) [21]. In a crisp logic a rule will be fired only if the premise is exactly the same as the antecedent of the rule. In fuzzy logic on the other hand, a rule is fired as long as there is a non-zero degree of

similarity between the premise and the antecedent of the rule [17].

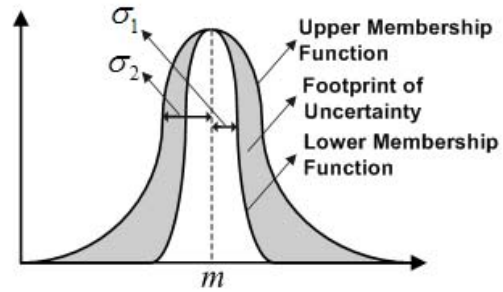


Fig. 3. Type-II Gaussian membership function, illustrating the lower and upper membership functions and the footprint of uncertainty.

In this study a singleton fuzzy system is considered, since the input parameters are single valued measurements. Also, all the fuzzy MFs are type-II functions, therefore, the GMP rule will be in the form of:

Premise:  $x_1$  is  $F_1$ , ...,  $x_n$  is  $F_n$ .

Implication: **If**  $x_1$  is  $\tilde{F}_1^j$ , ...,  $x_n$  is  $\tilde{F}_n^j$ , **Then**  $y$  is

$$\tilde{G}^j(x_1, \dots, x_n). \quad (6)$$

Consequence:  $y$  is  $\tilde{G}^{j*}(x_1, \dots, x_n)$ .

where  $F_i$ 's are fuzzy singletons (which are equivalent to crisp numbers) and  $\tilde{F}$  and  $\tilde{G}$  represent type-II fuzzy sets.

### C. Fuzzy Inference System

Fuzzy inference mechanism, also referred to as fuzzy model, applies the fuzzy reasoning on the rules in the rule base in order to derive a mathematically reasonable output or conclusion which represents the problem conditions best. Different fuzzy inference systems exist in the literature, such as Mamdani, Takagi-Sugeno and Tsukamoto fuzzy models [22]. In this study, the Mamdani min-max method is adopted [17].

For the specific case of interval type-II singleton fuzzy systems, the method can be simplified as follows:

For the  $k^{\text{th}}$  rule in the rule base, every input  $x_i$  (a singleton with the value of  $F_i$ ) intersects with its corresponding type-II MF  $\tilde{F}$  at two points:

$\underline{\mu}_{\tilde{F}_i}(F_i)$ : Intersection of the fuzzy singleton  $F_i$  with the

lower MF for the  $k^{\text{th}}$  type-II MF, and

$\bar{\mu}_{\tilde{F}_i}(F_i)$ : Intersection of the fuzzy singleton  $F_i$  with the upper MF for the  $k^{\text{th}}$  type-II MF.

Based on the Mamdani inference mechanism, the result of the input and antecedent operations, i.e., the firing strength of rule  $j$ , is an interval type-I set:

$$F^j(x) = \begin{cases} 1 & x \in [\underline{f}^j, \bar{f}^j] \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where:

$$\underline{f}^j = \min[\underline{\mu}_{\tilde{F}_1}(F_1), \dots, \underline{\mu}_{\tilde{F}_n}(F_n)], \quad (8)$$

$$\bar{f}^j = \min[\bar{\mu}_{\tilde{F}_1}(F_1), \dots, \bar{\mu}_{\tilde{F}_n}(F_n)]. \quad (9)$$

Figure 4 shows an illustrative example of the simplified case with two input variables for the  $j^{\text{th}}$  rule.

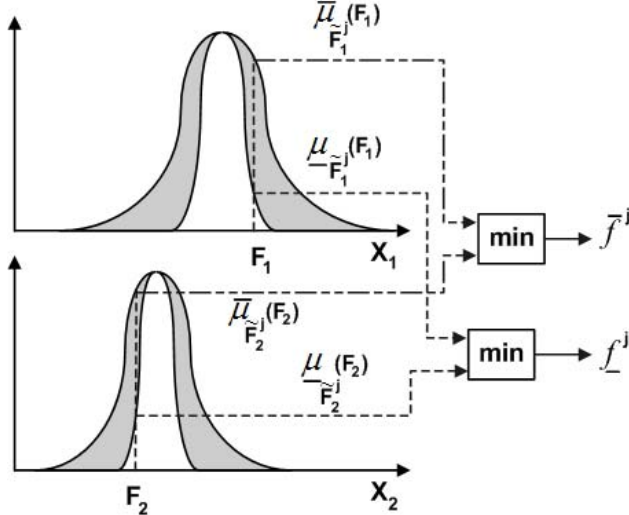


Fig. 4. Illustrative example of Mamdani inference mechanism applied to an interval type-II singleton fuzzy system with two inputs.

#### D. Type Reduction

The interval type-I set derived from calculating the firing strength of rule  $j$  should be converted to a crisp value. The first step is type reduction proposed by Karnik and Mendel [23]. This process takes the type-II output set and converts it to a type-I set that is called the type-reduced set:

$$Y_{\text{type-reduced}} = \begin{cases} 1 & y \in [\underline{y}, \bar{y}] \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

Several methods exist in the literature that can be employed for type-reduction, including centroid, center-of-sets, height and modified height [23]. The details of type-reduction for the general case of type-II fuzzy sets and the special case of interval type-II fuzzy sets are explained in [17],[18]. Nevertheless, the required steps for type-reduction using the center-of-sets method are briefly explained here:

- Step 1: calculate the centroid of the type-II interval consequent sets  $\tilde{G}^j$ . A brief summary of deriving the centroids in the special case of the interval type-II singleton fuzzy systems is presented in Appendix A. For detailed procedure of calculating the centroids in the general case the reader is referred to [17]. The results are interval type-I fuzzy sets for each consequent set:

$$C_{\tilde{G}^j}(y) = \begin{cases} 1 & y \in [\underline{g}^j, \bar{g}^j] \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

This is a one time calculation and does not impose a burden on the simulation process.

- Step 2: The lower and upper bounds of the type-reduced interval type-I set can be derived as:

$$\underline{y} = \frac{\sum_{j=1}^m \underline{g}^j \cdot \underline{f}^j}{\sum_{j=1}^m \underline{f}^j} \quad \text{and} \quad \bar{y} = \frac{\sum_{j=1}^m \bar{g}^j \cdot \bar{f}^j}{\sum_{j=1}^m \bar{f}^j}, \quad (12)$$

where  $m$  is the number of rules in the rule base.

#### E. Defuzzification

Since the resultant type-reduced output is an interval type-I fuzzy set, it can be easily defuzzified using the average of its lower and upper bounds [18]:

$$y = \frac{\underline{y} + \bar{y}}{2}. \quad (13)$$

### IV. STATCOM IN A MULTIMACHINE POWER SYSTEM

The power system considered in this study is a 10-bus multimachine with two generators and an infinite bus (Fig. 5). The generators are modeled in details, with exciter, AVR and governor dynamics taken into account. The details of the power system can be found in [24].

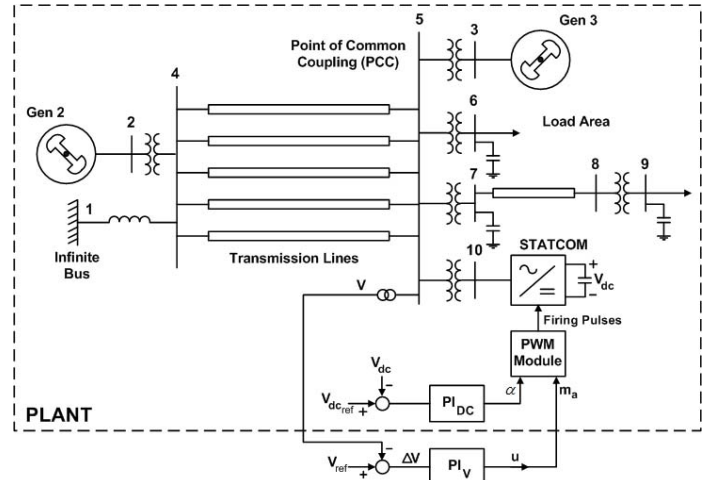


Fig. 5. STATCOM in a multimachine power system.

The STATCOM is assumed to be primarily controlled by the scheme shown in Fig. 5, where two decoupled PI controllers try to control the line voltage at the point of connection to the power system and the dc link voltage inside the device respectively. Controlling the voltage at the point of common coupling (bus 5 in Fig. 5) is considered the main objective of the STATCOM.

The proposed type-II fuzzy controller will replace the PI controller of the line voltage control loop only ( $PI_V$ ). The dc link control is considered to be performed by the conventional  $PI_{DC}$ , since it is related to the internal structure of the STATCOM and as opposed to the power system, the STATCOM does not go through fast dynamics changes.

### V. STATCOM TYPE-II FUZZY LOGIC CONTROLLER

The proposed fuzzy controller has two inputs, the line voltage error  $\Delta V(t)$  and the change in the line voltage error  $\Delta E(t) = \Delta V(t) - \Delta V(t-1)$ . Adding the latter helps the controller to respond faster and more accurately to the disturbances in the system. A time step of 20.0 ms (corresponding to a sampling frequency of 50 Hz) is selected for calculating the change in error. Figure 6 shows the schematic diagram of the proposed STATCOM type-II fuzzy controller.

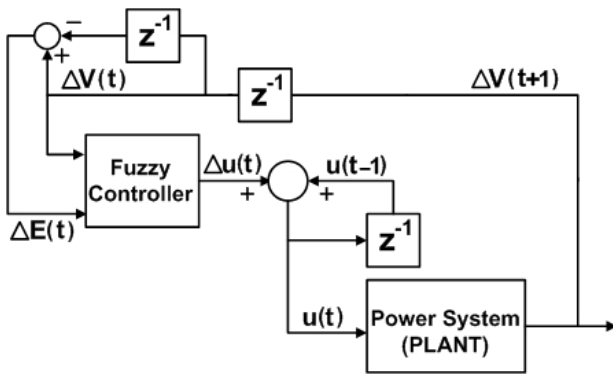


Fig. 6. Schematic diagram of the STATCOM fuzzy controller.

A proportional-integrator approach is applied in order to enable the fuzzy controller to deal with the actual signals rather than deviation signals. This is achieved by adding the instantaneous controller output  $\Delta u(t)$  to the previously accumulated total control signal (Fig. 8).

$$u(t) = u(t-1) + \Delta u(t) \quad (14)$$

where the final control output  $u(t)$  replaces the inverter modulation index in Fig. 7.

Six and three membership functions are assigned to the line voltage deviations  $\Delta V(t)$  and the change in the line voltage error  $\Delta E(t)$  respectively, while seven membership functions are considered for the controller output  $\Delta u(t)$ . The rule base implemented for the fuzzy controller is shown in Table I.

TABLE I  
FUZZY LOGIC CONTROLLER RULE BASE<sup>1</sup>

Fuzzy Inputs/ Output	$\Delta V$						
	NM	NS	Z	PS	PM	PB	
$\Delta E$	NM	NB	NM	Z	PS	PM	PB
	Z	NM	NM	Z	PM	PM	PB
	PM	NM	NS	Z	PM	PB	PB

<sup>1</sup>These membership functions are associated with the common terms *Negative Big* (NB), *Negative Medium* (NM), *Negative Small* (NS), *Zero* (Z), *Positive Small* (PS), *Positive Medium* (PM) and *Positive Big* (PB) for each variable.

Type-II Gaussian MFs are considered for all the input and output variables of the fuzzy controller (Fig. 4). Each membership function has a fixed mean and its corresponding uncertain standard deviation varies in a given range:

$$\mu_{\tilde{F}_i}(x_i) = \exp\left[-\frac{1}{2}\left(\frac{x_i - m_i^j}{\sigma_i^j}\right)^2\right] \quad (15)$$

where:

$j$ : Number of rules in the rule base,

$m_i^j$ : Fixed mean (center) of the Gaussian function corresponding to the  $i^{\text{th}}$  variable in the  $j^{\text{th}}$  rule,

$\sigma_i^j \in [\sigma_{i1}^j, \sigma_{i2}^j]$ : Variable standard deviation of the Gaussian function corresponding to the  $i^{\text{th}}$  variable in the  $j^{\text{th}}$  rule.

Table II summarizes the centers and the ranges of the MF centers and widths for the input variables.

TABLE II  
FUZZY INPUT MEMBERSHIP FUNCTION PARAMETERS

FUZZY INPUT VARIABLES	$\Delta V$			$\Delta E$		
	$m$	$\sigma_1$	$\sigma_2$	$m$	$\sigma_1$	$\sigma_2$
NM	-0.5	0.2	0.3	-0.04	0.03	0.05
NS	-0.15	0.1	0.14	---	---	---
Z	0.0	0.02	0.06	0.0	0.03	0.05
PS	0.15	0.1	0.14	---	---	---
PM	0.5	0.2	0.3	0.04	0.03	0.05
PB	1.0	0.3	0.4	---	---	---

Table III also summarizes the specifications of the type-II membership functions of the output variable. The details of calculating the centroids are provided in Appendix A.

TABLE III  
FUZZY OUTPUT MEMBERSHIP FUNCTION PARAMETERS

FUZZY OUTPUT VARIABLES	$\Delta u$		
	$m$	$\sigma_1$	$\sigma_2$
NB	-0.018	0.003	0.005
NM	-0.015	0.004	0.006
NS	-0.010	0.005	0.008
Z	0.004	0.007	0.010
PS	0.010	0.005	0.008
PM	0.015	0.004	0.006
PB	0.018	0.004	0.005

## VI. SIMULATION RESULTS

The performance of the proposed type-II fuzzy controller is compared with the fine tuned PI controller for the line voltage deviations and the simulation results are presented here.

The  $PI_v$  controller is fine tuned at only one operating point. In the first test, a step 5% step change is applied to the STATCOM voltage reference at 1 sec, followed by a -6% step at 3 sec. The performance of the two controllers is compared in Fig. 7. It can be seen that although the fuzzy controller is slightly faster in responding to the change, the  $PI_v$  has an acceptable performance as well. This is due to the fact that the PI controller is fine tuned in that operating condition.

However, in the second test, a 100 ms three phase short circuit is applied to the terminals of generator 3. This is a large enough disturbance to momentarily move the system away from its designed operating condition. Figure 8 shows the voltage at bus 5 where the STATCOM is connected to the power system. It can be seen that the proposed fuzzy controller is more effective in damping out the low frequency oscillations compared to the  $PI_v$  controller. Clearly, a  $PI_v$  with a much lower bandwidth (slower response) can be designed to counteract the large scale disturbances. But such an approach will reduce the efficiency of the controller during small scale disturbances, such as step changes. Therefore, in designing a PI controller there should always be a tradeoff between the time response of the controller during small scale disturbances and the overshoot caused during the large scale faults.

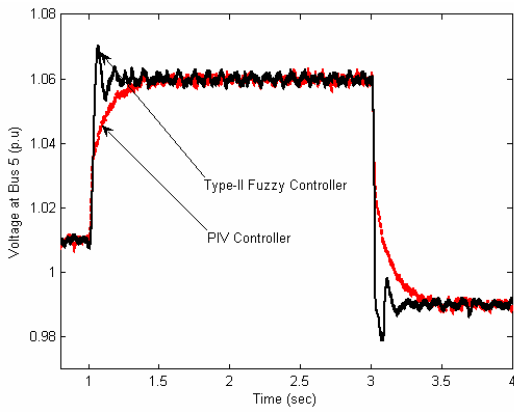


Fig. 7. Voltage at bus 5 during a step changes applied to the line voltage reference.

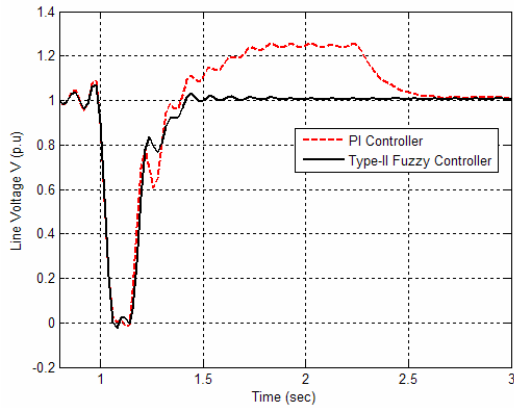


Fig. 8. Voltage at bus 5 during a 100 ms three phase short circuit at the terminals of generator 3.

One of the measures by which the performances of the two controllers can be evaluated is the control effort provided by each one. Figure 9 shows the reactive power injected by the STATCOM into the power network by the two controllers. It is clear that the fuzzy controller brings the system to steady state with less amount of reactive power injection, which in turn means less current will pass through the STATCOM inverter switches. This can bring down the switch ratings and therefore the cost of the FACTS device.

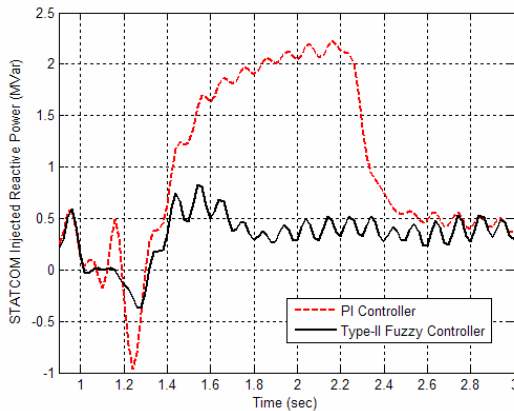


Fig. 9. Reactive power injected by the STATCOM during a 100 ms three phase short circuit at the terminals of generator 3.

The modulation index of the STATCOM inverter is another measure for comparison between the two controllers. Figure 10 shows that the PI controller forces the inverter into over-modulation for a considerably longer

period than the proposed fuzzy controller. This in turn causes more harmonic distortion for the power network.

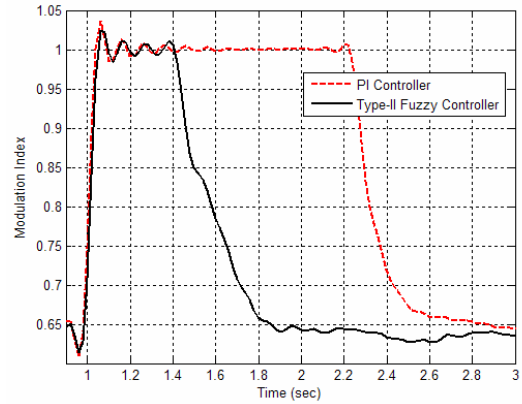


Fig. 10. STATCOM inverter modulation index during a 100 ms three phase short circuit at the terminals of generator 3.

The performance of the two controllers should also be compared when the system configuration has changed. This can be looked at as an uncertainty associated with the system/controller modeling, since the parameters of the two controllers are determined at a single operating condition. This has been achieved by a 100 ms three phase short circuit followed by disconnecting one of the parallel transmission lines connecting buses 4 and 5. Figures 11 and 12 show the simulation results.

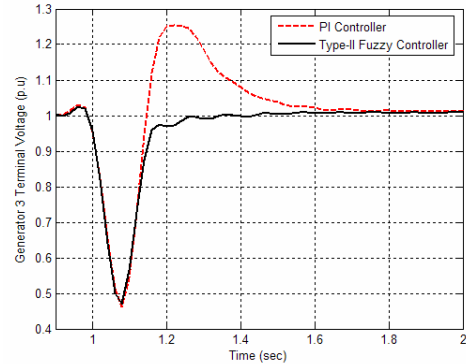


Fig. 11. Generator 3 terminal voltage during a 100 ms three phase short circuit at the middle of one of the transmission lines. The line is disconnected after the fault is cleared.

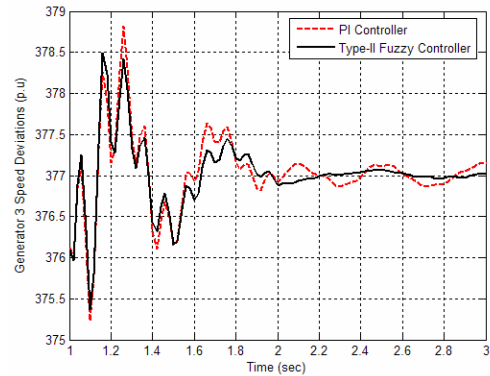


Fig. 12. Generator 3 speed deviations during a 100 ms three phase short circuit at the middle of one of the transmission lines. The line is disconnected after the fault is cleared.

It can be seen that the proposed type-II fuzzy controller is robust to the change in the operating condition and even though its parameters are not fine tuned for this point, it still

manages to restore the system to steady state conditions faster than the PI<sub>v</sub>.

## VII. CONCLUSION

An interval type-II fuzzy logic based controller was proposed in this study that can perform as a robust controller for a STATCOM in a multimachine power system. The uncertainties in the power system model can be incorporated into the fuzzy controller design by defining type-II membership functions. These fuzzy sets have footprints of uncertainties associated with them and therefore, are robust to changes in the plant dynamics. Whereas an ordinary fuzzy controller performs like a nonlinear gain scheduling controller whose parameters are still dependent on the operating conditions of the system.

The proposed type-II fuzzy controller replaces the line voltage controller of the STATCOM. Simulation results are provided that indicate the fuzzy controller is more effective in damping out the oscillations occurred as a result of small scale and large scale disturbances. The superior performance of the fuzzy controller even prevails when the operating conditions of the power system are changed. This is the point where a PI controller fine tuned at a single operating condition fails to function properly.

Detailed step by step design procedure is provided for implementing an interval type-II fuzzy logic based controller, which can be applied to any problem.

## APPENDIX

### A. CENTROID OF A TYPE-II FUZZY SET

It was seen in section III.D that one of the steps required for type-reduction is calculating the centroid of the type-II consequent sets  $\tilde{G}^j$ . In this section, a simple step by step approach is presented for calculating the centroid of a general type-II membership function  $\tilde{G}$  which can represent any of the consequent type-II sets mentioned in section III. This procedure is explained based on the main theorems and general discussions in [17],[20].

Figure 13 shows a typical type-II MF with the footprint of uncertainties associated with it.

The input variable  $y$  can be discretized into  $p$  points throughout its universe of discourse. It was seen that associated with each point  $y_i$ , there's a type-I fuzzy set  $G_i$  that defines the range  $U_i=[u_{i1},u_{i2}]$  in which the fuzzy membership grade of  $y_i$  varies along with the probability of each membership grade (secondary membership function). Each range  $U_i$  can be further discretized into  $q_i$  points. An *embedded type-I* set  $G_e$  within the set  $\tilde{G}$  can be formed by randomly selecting  $p$  points, where each one belongs to a specific  $U_i$  (Fig. 13). The centroid of each set  $G_e$  can be written as:

$$C_{G_e}^k = \frac{\sum_{i=1}^p u_{ik} \cdot y_i}{\sum_{i=1}^p u_{ik}}, \quad (16)$$

where  $u_{ik}$  belongs to the  $k^{\text{th}}$  set of randomly selected points and lies within the range  $U_i=[u_{i1},u_{i2}]$ . In general there can be  $p \times q$  different embedded type-I sets  $G_e$ , whose centroids need to be calculated.

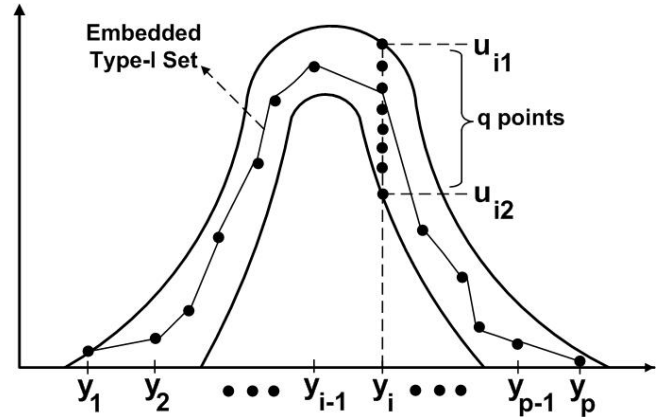


Fig. 13. Computation of the centroid of a type-II fuzzy set.

Each centroid  $C_{G_e}$  has a membership grade associated with it that can be directly derived from the corresponding membership grades of the points  $u_{ik}$ , which can be expressed as:

$$\mu(C_{G_e}^k) = \min[\mu_{G_1}(u_{1k}), \dots, \mu_{G_i}(u_{ik}), \dots, \mu_{G_p}(u_{pk})] \quad (17)$$

In the general case, the centroid of the type-II fuzzy set  $\tilde{G}$  can be written as:

$$C_{\tilde{G}} = \sum_{k=1}^{p \times q} \mu(C_{G_e}^k) / C_{G_e}^k, \quad (18)$$

Clearly, equation (17) is computationally intensive and might not be appropriate in an online application. However, the introduction of the interval type-II sets, drastically reduces the computational burden, since the membership grades of the points  $u_{ik}$  are now constant, i.e., unity. Hence, equation (18) is simplified to:

$$C_{\tilde{G}} = \sum_{k=1}^{p \times q} 1 / C_{G_e}^k, \quad (19)$$

which means the calculation is now reduced to calculating the centroids of the embedded type-I sets only. Naturally, this is a one time calculation, since the membership functions are not changed during the simulation time. Figure 16 shows a typical type-II function with its corresponding center.

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