Voltage Stability Improvement by Optimized STATCOM Controller for Grid Connected Hybrid Network System

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Abstract

In a renewable energy system, the major task to maintain the voltage regulation of the system and other hands improvement of system stability. A proposed new STATCOM with advanced control technique are introduced in this paper. It is to mitigate the bus voltage variations caused by the large disturbances. A proposed STATCOM consists of voltage regulator and current regulator. Here, the current regulator is to produce the phase angle of voltage source converter, while the voltage regulator outputs the current reference on the quadrature axis of the devices. The voltage and current regulator parameters are treated as a membership function. This membership functions involving by dual fuzzy algorithm (Type-2 Fuzzy controller) which reduces the voltage regulation caused by large disturbances. The proposed controller obtains the faster and more stable responses so that the reactive power required by the proposed method is to stabilize the voltage.

Keywords: *STATCOM, Type II Fuzzy Set, Particle Swarm Optimization (PSO)*

1. Introduction

The photovoltaic (PV) cells are placed generally where there will be meteorological conditions such that to extract more amount power from the cells by using the Maximum Power Point Tracking (MPPT) system. A coherent strategy, Interval Type-II (IT2) Fuzzy Logic System (FLS) is employed in addition to the MPPT system for the PV cell to gain the maximum power point. The IT2 Fuzzy is involved with the particle swarm optimization (PSO) to run the STATCOM in a smoother way.

Basically, the static synchronous compensator (STATCOM) belongs to the FACTS Family, which compensates and injects the reactive power to a grid in a power system. The STATCOM controls the actual power flow in the system. The prime role of a STATCOM is to control the voltage regulation and also to stabilize the voltage supplied to the load or grid connected system. In this paper, to make effective and efficient use of a STATCOM, in general known as Optimized STATCOM, is done by the PSO technique which in-turn results the better utilization of the system. Most probably the STATCOM has the voltage regulator and the current regulator to measure the voltage reference at the output and the phase angle of the STATCOM respectively.

The T1 FLS normally has 5 membership functions, to increase the voltage stability we switch over to the dual fuzzy i.e., IT2 FLS has 25 membership functions on a whole. The membership functions are considered as the upper and lower membership functions. The voltage regulator and the current regulator parameters are taken as the upper and lower membership functions.

2. IT2 FUZZY LOGIC SYSTEM

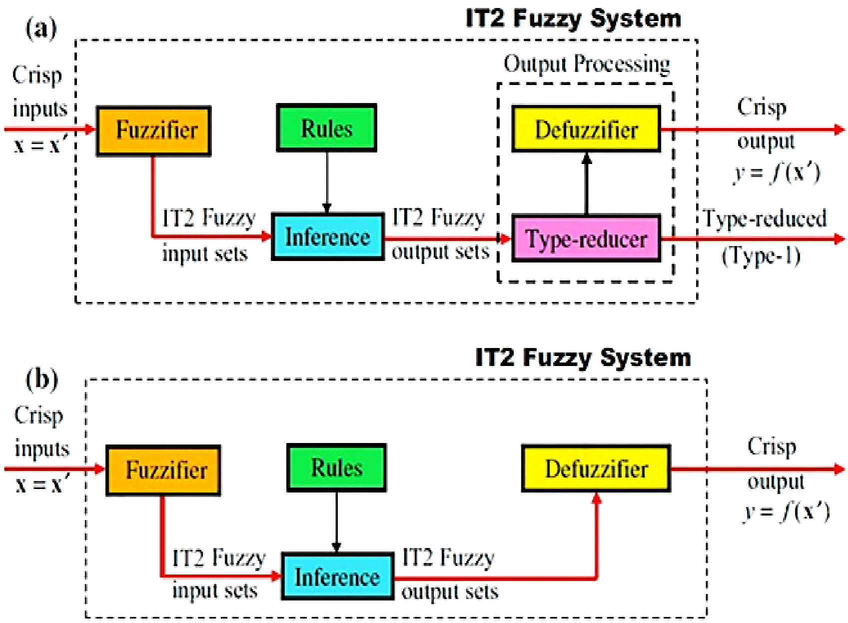

Fig. 1(a), (b) IT2 Fuzzy set

The mentioned figure1 describes about the fuzzy set and the fuzzifier process. The fig.1(a) explains that after the fuzzification process it undergoes type reduction and then defuzzification while the fig.1(b) makes clear that after the fuzzification process direct defuzzification proceeds. A crisp input is given to the fuzzifier, from there it is lend to the interference engine mainly Mamdani interference engine, takes the crisp input and archives the fuzzy rules to the input and its output is given as the input to the type reducer to obtain the T1 FLS. Then its been send to the de-fuzzifier where the converted IT2 to T1 FLS is taken and evaluated the true numbers.

At Fuzzification process:

Inference block assigns fuzzy inputs to fuzzy outputs using the rules in the rule base and the operators such as union and intersection. In type-2 fuzzy sets, join (⊔) and meet operators (⊓), which are new concepts in fuzzy logic theory, are used instead of union and intersection operators. The set of new operators are used in secondary membership functions.

$$X = (X_1, X_2, \ldots\ldots. X_n) \in (X_1 \times X_2 \ldots\ldots. X_n) \ldots\ldots \quad (1)$$

At Interference Engine:

The inference engine and the rules that allow the mapping from input T2FS to the output T2FS. Each rule in a fuzzy rule base with the M rules having the inputs as

$X = (X_1, X_2, \ldots\ldots. X_n) \in (X_1 \times X_2 \ldots\ldots. X_n)$

and output as $y_k \in Y_K$, they can be written as follows:

$$R_k^i : \tilde{F}_1^i * \tilde{F}_2^i * \ldots\ldots * \tilde{F}_n^i \rightarrow \tilde{G}_K^i = \tilde{A}^i \rightarrow \tilde{G}_K^i \ldots\ldots \quad (2)$$

where $\tilde{F}_j^i$ is the jth T2FS, j = 1, ... , n, which is defined by a lower and upper bound membership function:

$$\mu_{\tilde{F}_j^i}(X_j) = \left[\underline{\mu}_{\tilde{F}_j^i}(X_j), \overline{\mu}_{\tilde{F}_j^i}(X_j)\right],$$

i = 1, 2, 3,..., M; k = 1, ... , c ………………………………………………….. (3)

Compute the firing interval of the ith rule, where $*$ denotes the product operation:

$$\underline{f}(x) = \underline{\mu}_{\tilde{F}_1^i}(X_1) * \mu_{\tilde{F}_2^i}(X_2) * \ldots\ldots \underline{\mu}_{\tilde{F}_n^i}(X_n)$$

$$\overline{f}^i(x) = \overline{\mu}_{\tilde{F}_1^i}(X_1) * \overline{\mu}_{\tilde{F}_2^i}(X_2) * \ldots\ldots \overline{\mu}_{\tilde{F}_n^i}(X_n) \ldots\ldots \quad (4)$$

At type reducer:

The Type-2 fuzzy outputs of the inference engine are transformed into Type-1 fuzzy sets that are called the type-reduced sets. There are two common methods for the type-reduction operation in the T2FLSs: One is the Karnik- Mendel iteration algorithm, and the other is Wu-Mendelun certainty bounds method. There are as many type-reduction methods as there are type-1 defuzzification methods. An algorithm developed by Karnik and Mendel now known as the KM Algorithm is used for type-reduction. Although this algorithm is iterative, it is very fast. These two methods are based on the calculation of the centroid.

At de-fuzzification:

The second step of output processing, which occurs after type-reduction, is still called defuzzification. Because a type-reduced set of an Interval type-2 fuzzy set is always afinite Interval of numbers, the defuzzified value is just the average of the two end-points of this Interval. The outputs of the type reduction block are given to defuzzificaton block. The type-reduced sets are determined by their left end point and right end point, the defuzzified value is calculated by the average of these points. In a Type-1 FLS, output processing, called defuzzification, maps a type-1 fuzzy set into a number. There are many ways for doing this, e.g., by computing the union of the fired-rule output fuzzy sets (the result is another type-1 fuzzy set)and then computing the center of gravity of the membership function for that set; computing a weighted average of the center of gravities of each of the fired rule consequent membership functions; etc.

Things are somewhat more complicated for a Type-2 FLS, because to go from a Type-2 fuzzy set to a number (usually) requires two steps. The first step, called type-reduction, is where a type-2 fuzzy set is reduced to a type-1 fuzzy set. In most engineering applications of a FLS, a number and not a fuzzy set is needed as its final output, e.g., the consequent of the rule given above is "Rotate the value a bit to the right." No automatic value will know what this means because "a bit to the right" is a linguistic expression, and a value must be turned by numerical values, i.e. by a certain number of degrees. Consequently, the fired-rule output fuzzy sets have to be converted into a number, Output Processing block.

It is clear that there can be two outputs to a type-2 FLS which are crisp numerical values and the type-reduced set. The latter provides a measure of the uncertainties that have flowed through the Interval type-2 FLS, due to the uncertain input measurements that have activated rules whose antecedents or consequents or both are uncertain. As standard deviation is widely used in probability and statistics to provide a measure of unpredictable uncertainty about a mean value, the type-reduced set can provided a measure of uncertainty about the crisp output of a type-2 FLS.

$$Y_K(X) = \frac{Y_{kl}+Y_{kr}}{2}, k = 1, \ldots . c \qquad \ldots\ldots (5)$$

3. PROPOSED SYSTEM

3.1. MODEL OF STATCOM

A STATCOM usually consists of a coupling transformer, capacitor, voltage source converter, load. The Optimized STATCOM consists of a phase locked loop, Park Transform, Voltage Regulator, Current Regulator, DC Regulator, Pulse Generator, serial bus as shown in fig 3(a).

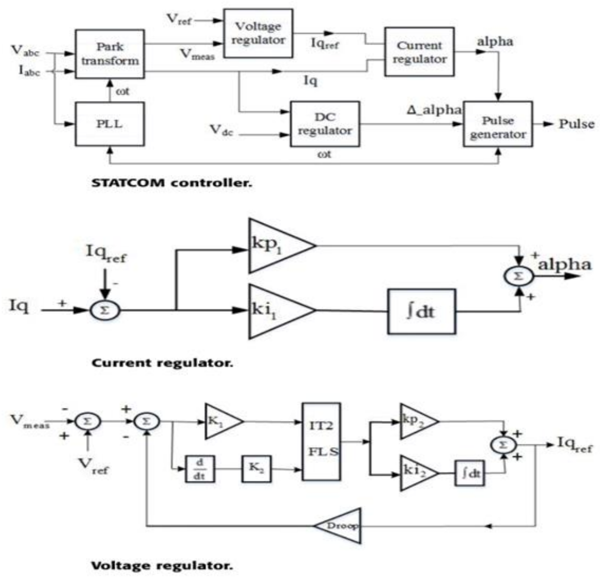

Fig. 3(a),(b),(c). Block diagram of an optimized STATCOM

The park transform is to indicate the voltage and current parameters on the direct, quadrature & zero axes by using the three phase sequences in the form of abc to dq or dq to zero transform from the pulse generator as a 2 rotating axes. The current regulator is used to measure the phase angle of the grid connected system at its output which clear gives a view in the fig 3(b). The voltage regulator regulates the required amount of voltage to the grid. In voltage regulator we introduced the IT2 FLS so that the voltage regulator minimizes voltage regulations as much as possible and stabilize the voltage for its better improvement and utilization. The IT2 FLS is connected feedback to the voltage and current regulators as it can be seen from the fig 3(c) such that the membership functions of the fuzzy set is the STATCOM parameters.

3.2. TUNING PARAMETERS BY PSO

The Conventional optimization methods (such as, gradient fit) can't be used for setting the parameters A_1~ A_2, B_1~B_2, Kp_1, Ki_1, Kp_1, Ki_2, k_1 and k_2, since the objective function is undeclared. The PSO is inherited here, to identify the above undefined parameters. The PSO technique would discover the global optimum and concurrently exploit the local or known optima. In contradiction to this, other traditional evolutionary algorithms (like genetic algorithms) was being generally considered slighter efficient. The PSO, is an evolution-based optimization criteria which utilizes a population of particles (possible and realistic solutions), whose historical information will be updated by the continuous iterative operation and which move in a ψ dimensional solution space. Let's say, the superscript $t$is to be the iteration index andthe position and velocity of each particle $t$are updated as follows,

$$V_p^{t+1} = w^t v_p^t + c_1 r_1^t \left(p_{best}^t - X_p^t\right) + c_2 r_2^t \left(g_{best}^t - X_p^t\right) \quad \text{……..……………… (i)}$$

$$X_p^{t+1} = X_P^t + V_p^{t+1} \quad \text{………………..………………………………………. (ii)}$$

Where the vectors,

X_P Isø dimensional position of particle, V_P is ø dimensional velocity of particle
Here p=1, 2, 3,…., (population size)

The inertia weight w copies the characteristics in the preceding iterations to the present iteration. The greater the ω corresponds too much stronger impact of proceeding V_p^t on V_p^{t+1} .p_{best} And g_{best} are the best and suitable position of a particle at present and the best-known position that would be found by any particle in the swarm as compared respectively. The values of $r_1$and r_2 are randomly given within [0, 1]. The Learning factors $c_1$and $c_2$are the positive constants within the interval [0, 2] and$c_1 + c_2 \leq 4$.
$c_1 r_1^t (p_{best}^t - X_p^t)$ The term refers to the local search and $c_2 r_2^t (g_{best}^t - X_p^t)$ term in (i) exhibits the global search (exploitation) in a ψ - dimensional search space. The global search shall coordinate with the local search, to avoid premature results &reach the global optimum. The inertia weight w describes the momentum of the particle and decreases linearly during the iterations, in order that the PSO at first executes global searches, by changing gradually over to the local searches. Here, -$X_P$denotes a vector whose elements are A_1~ A_2, B_1~B_2, Kp_1, Ki_1, Kp_1, Ki_2, k_1 and k_2. As assumed, ψ= 12. The initial inertia weight $w$and population size are 0.92 and 30, respectively. c_1Andc_2 are 1.2 and 0.12, respectively. The fitness (objective) in this study is the total sum of Integral Absolute Errors (IAE) in both the current regulator and the voltage regulator, as follows.

$$\int \left| (V_{ref} - V_{meas}) - I_{qref} * D_{roop} \right| dt + \int \left| I_q - I_{qref} \right| dt \ldots\ldots\ldots\ldots\ldots\ldots \text{(iii)}$$

3.3. IT2 FUZZY SET

The IT2 FLS-based voltage regulator to mitigate the voltage fluctuation, as shown in Fig.4

	x1= NL	x1= NS	x1= ZR	x1= PS	x1= PL
x2= PL	NL	NL	NL	NS	ZR
x2= PS	NL	NL	NS	ZR	PS
x2= ZR	NL	NS	ZR	PS	PL
x2= NS	NS	ZR	PS	PL	PL
x2= NL	ZR	PS	PL	PL	PL

Fig. 4(a) Twenty-Five Fuzzy Rules Set

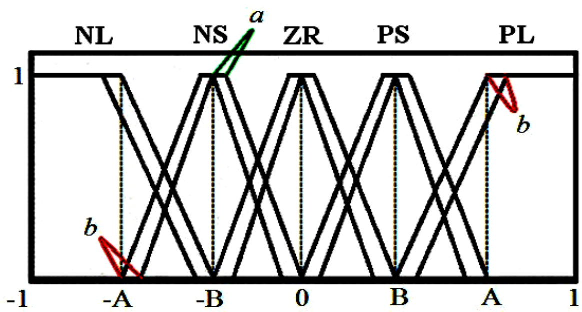

Fig. 4(b) UMFs & LMFs of the Fuzzy Set

The proposed IT2 fuzzy rule can be expressed as

IF x_1=$\tilde{F}_{1n}$ and x_2=$\tilde{F}_{2n}$then y is $\tilde{Y}_n$.n=1, 2… 25.

$$x_1 = K_1 \times \left(\left(V_{ref} - V_{meas} \right) - Iq_{ref} \times D_{roop} \right) \right)\text{..................................} \quad \text{(iv)}$$

Denoted as $K_1 \times Äe$ andx_2 is the rate of change of $K_2 \times Äe$. The variable y is the input applied to the PI controller with gains kp_2 and ki_2.

A total of 25 IT2 fuzzy rules are implemented in the proposed method (i.e., N=25), as shown Table I. The symbols NL, NS, ZR, PS, and PL, represents "Negative Large", "Negative Small", "Zero", "Positive Small", and "Positive Large", respectively. All the UMFs of$\tilde{F}_{1n}$,$\tilde{F}_{2n}$and $\tilde{Y}_n$ are illustrated as the trapezoid functions, while the corresponding LMFs of NS, ZR and PS are the triangular ones, as shown in Fig. 6. The parameters a and b denote the tolerances (uncertainties) between the UMF&LMF. Restated, the values of a and b influence the FOU. Notably, these IT2 membership functions are symmetrical. The right boundaries of fuzziness for $\tilde{F}_{1n}$, $\tilde{F}_{2n}$and $\tilde{Y}_n$are A_1, A_2 and A_3, respectively. The centers of PS for$\tilde{F}_{1n}$,$\tilde{F}_{2n}$ and $\tilde{Y}_n$ are B_1, B_2 and B_3, respectively. Accordingly, a total of 12 unknown variables must be determined. They are A_1~A_3, B_1~B_3, kp_1, ki_1, kp_2, ki_2, K_1 and K_2, which are determined by particle swarm optimization (PSO) here in.

4. SIMULATION RESULTS

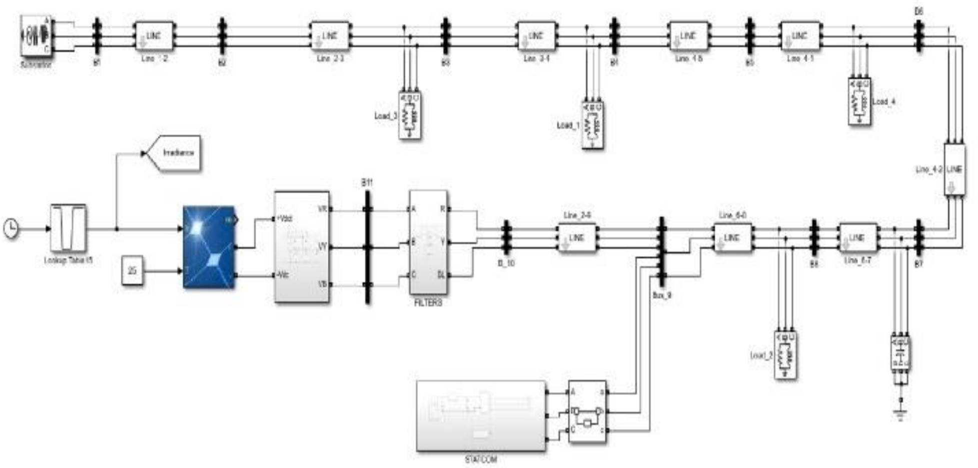

Fig. 5(a) MATLAB/SIMULINK circuit diagram of the proposed system

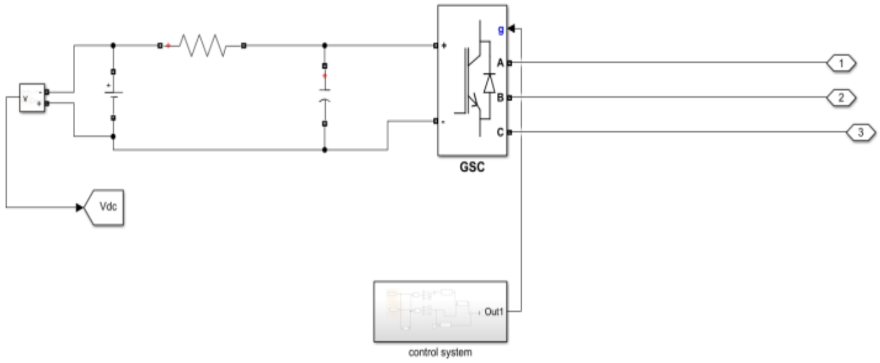

Fig. 5(b) STATCOM subsystem

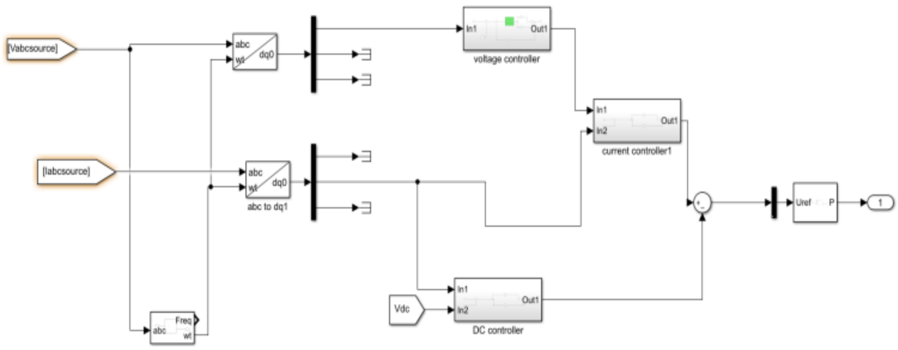

Fig. 5(c) Controller subsystem

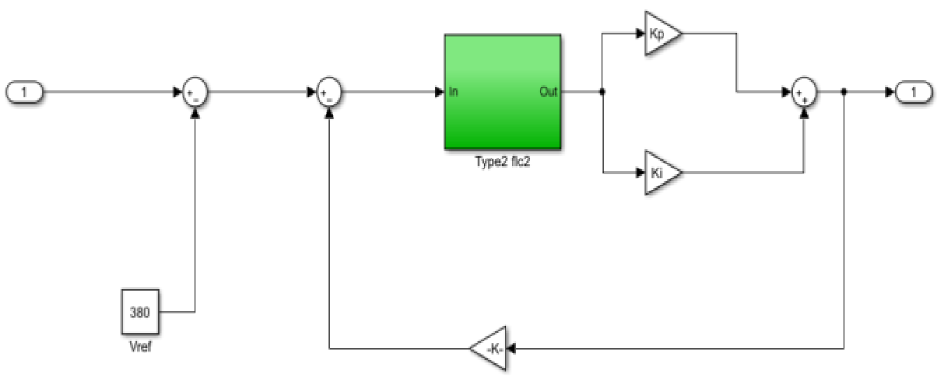

Fig. 5(d) Subsystem of type-II (IT2) fuzzy logic system (FLS)

A. IRRADIATION CHANGING

The irradiation is initially 1000W/m^2 and decreases linearly to 600 W/m^2 from 0.5s to 0.6 s and then increases linearly to 1000 W/m^2 from 1.2s to 1.3 s,. Figure 8 plots the corresponding real and reactive power generations from the PV farm. Table II presents ranges of the UMF and the LMF for x_1(that's, $\tilde{F}_{1n}$), x x_2(that's, $\tilde{F}_{2n}$)and $\tilde{Y}_n$. Each membership function is characterized by four numbers, which denote four points in the universe of disclosure. Because the LMFs of NS, ZR and PS are triangular, their 2nd and 3rd values are identical. The parameters of a and b, specified in Fig. 6 are 0.01 and 0.05, respectively.

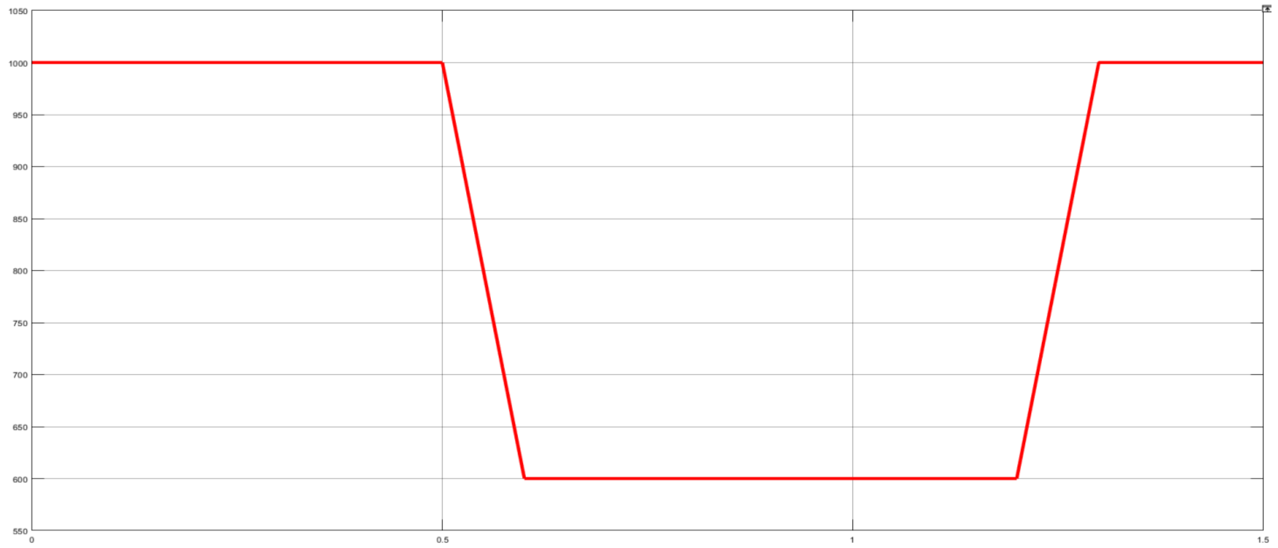

Fig. 6 Variations of irradiation in studied power system.

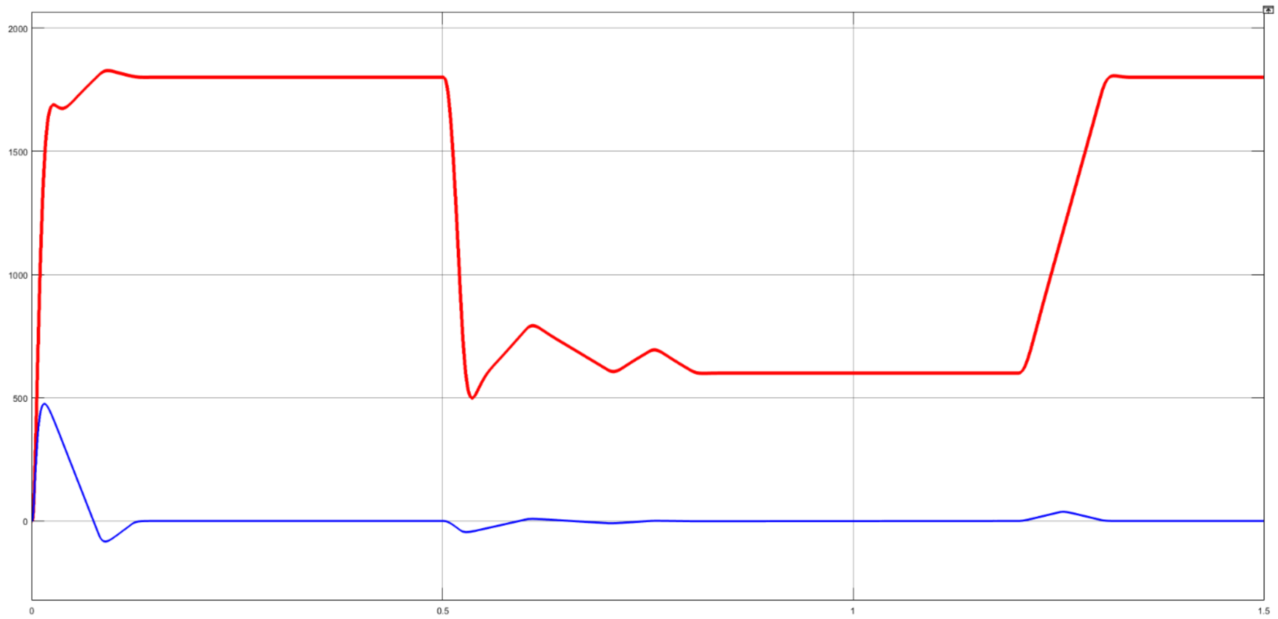

Fig. 7 Real power (kW) and reactive power(KVAR) generations.

Fig. 8 Voltage response of a STATCOM.

Fig. 9 Reactive power(KVAR) output from STATCOM.

B. IMPACT OF PARAMETERS A AND B ON RESPONSES OBTAINED BY PROPOSED IT2-FLS

The parameters of the upper/lower membership functions and control gains obtained by Sec. IV.A are applied to other operation conditions in this subsection. Because the daily load level is time-varying, system responses of the peak load and off-peak load are examined herein. Total levels of the peak and off-peak loads are assumed to be 1.5 and 0.5 times (i.e., 5.4MW + j2.025MVAR and 1.8MW + j0.675MVAR) the level of the scenario studied in Sec. IV.A. Figs. 11 and 12 show the voltage responses and reactive power output of the STATCOM for the peak-load case, respectively. Figs. 13 and 14 illustrate the voltage responses and reactive power output of STATCOM for the off-peak load case, respectively. It can be found that the proposed IT2 FLS-based controller still obtains faster and more stable responses, compared with the conventional PI and T1 FLS-based controllers, in spite of different operation conditions. The reactive power required by the proposed method to stabilize the voltage is the smallest among three methods.

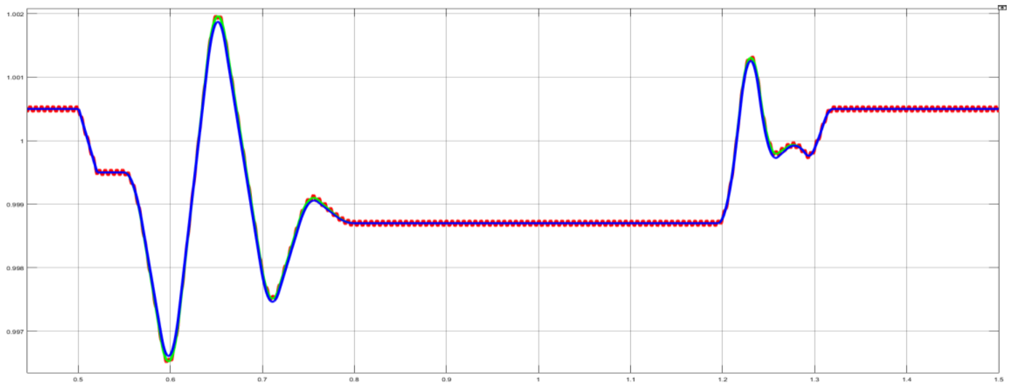

Fig. 10 Three voltage responses (p.u) by considering three different values of a and b

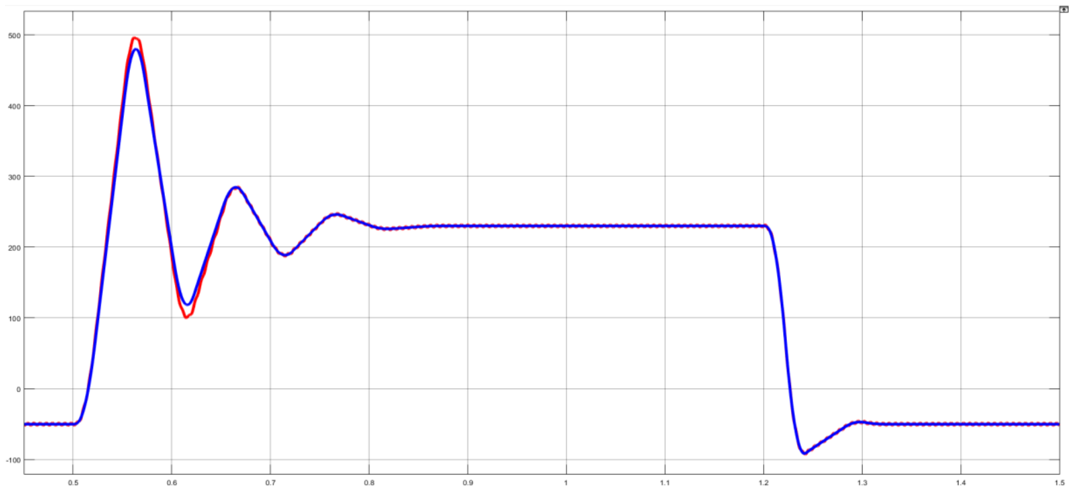

Fig. 11 Three reactive power responses (KVAR) obtained with three different values of a and b.

C. IMPACTS OF DIFFERENT OPERATION CONDITIONS ON RESPONSES OBTAINED BY PROPOSED IT2-FLS

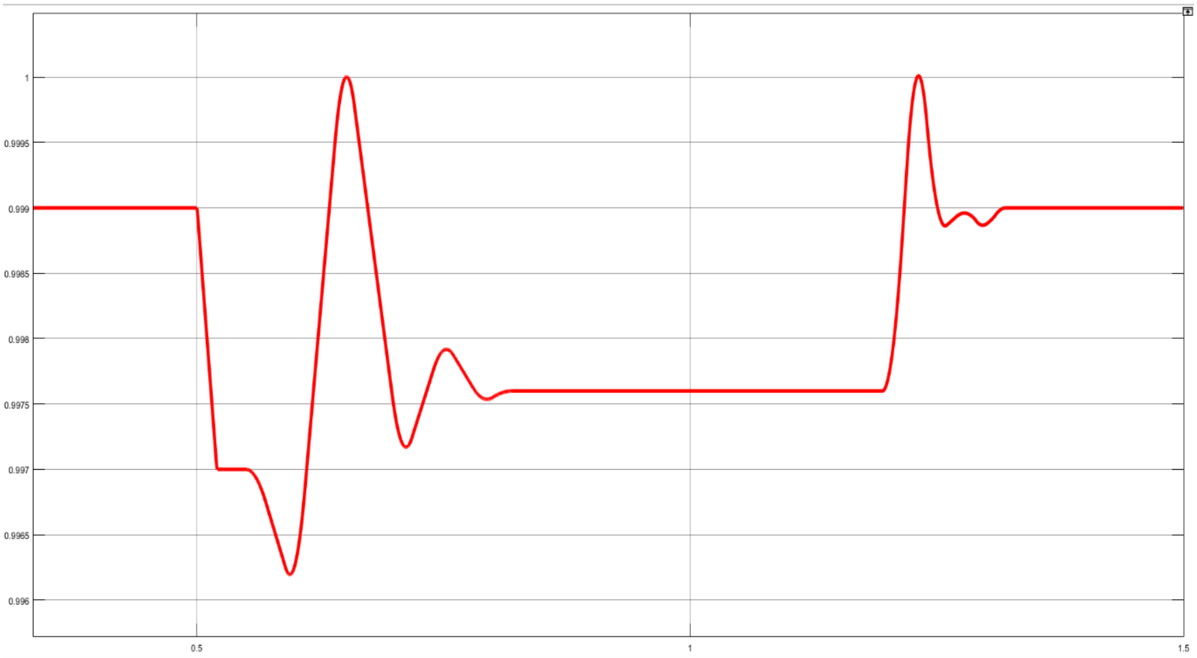

Fig. 12 Voltage response(p.u.) at (peak load).

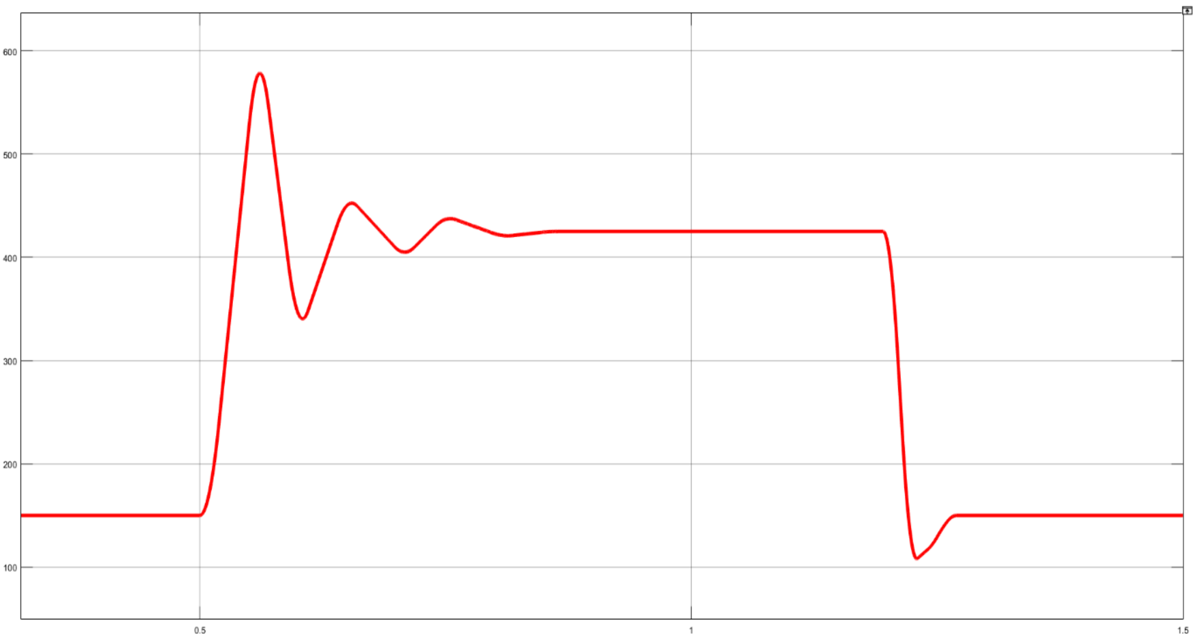

Fig. 13 Reactive power(KVAR) output from STATCOM (peak load).

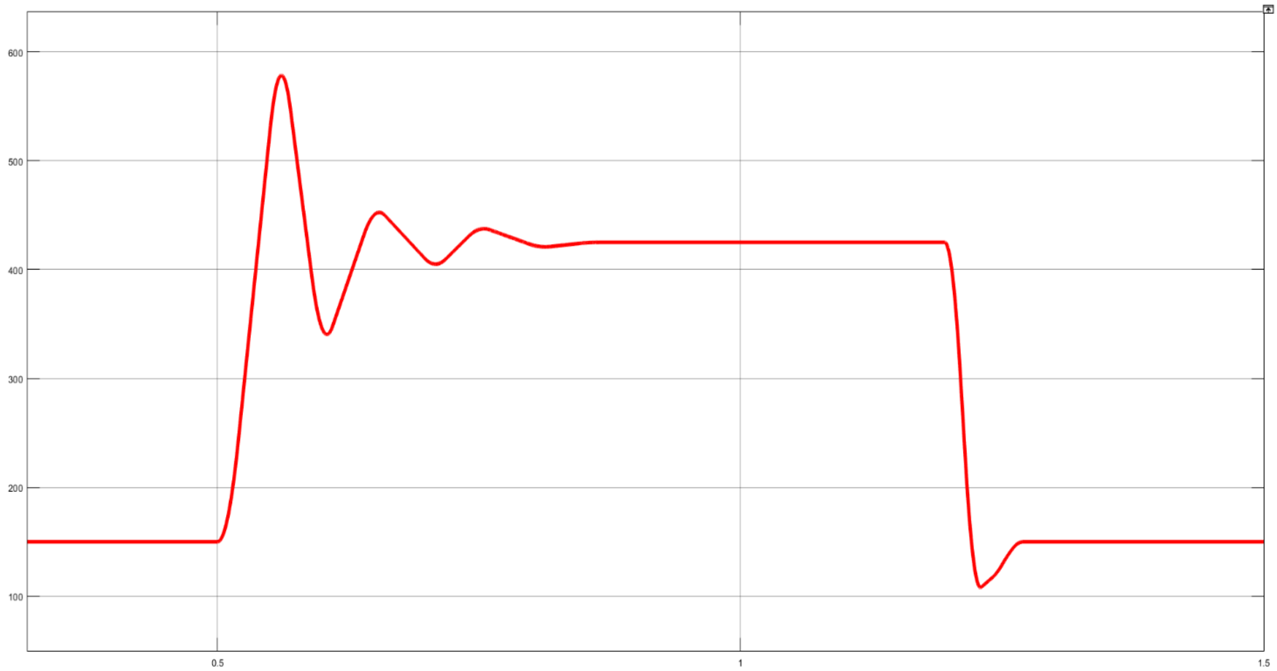

Fig. 14 Voltage response(p.u) at (off-peak load).

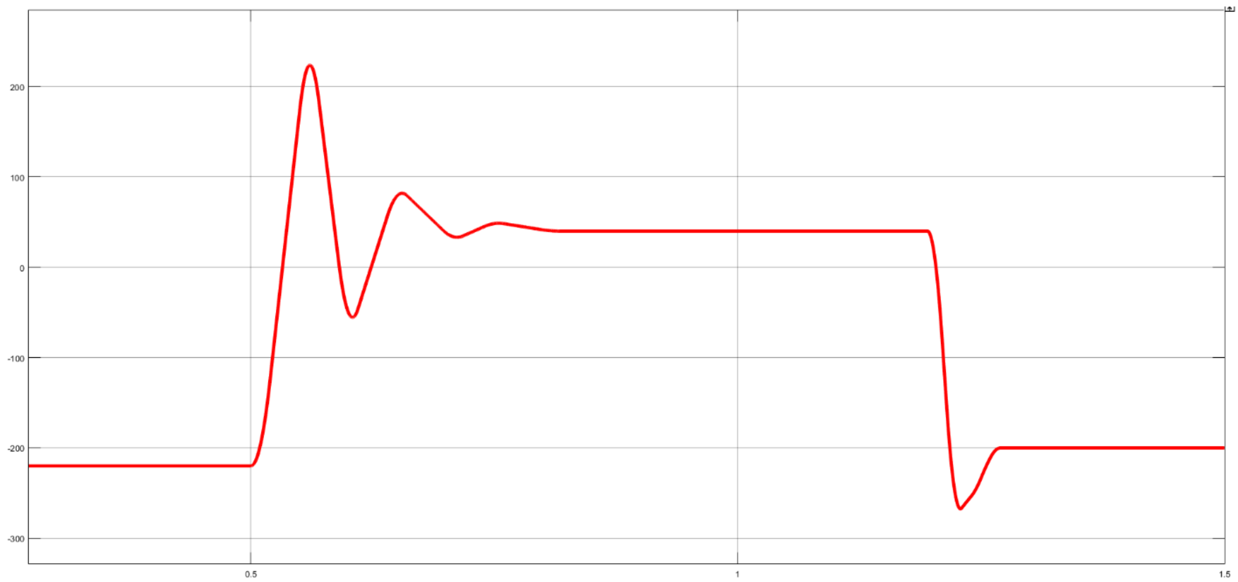

Fig. 15 Reactive power (KVAR) output from STATCOM (off-peak load)

5. CONCLUSIONS

An Interval Type-II (IT2) Fuzzy rule-based STATCOM is proposed to mitigate the voltage variations in this paper. The voltage error and the rate of change of the voltage error arte utilized to serve as the inputs for the IT2 Fuzzy rules; the action parts of the IT2 Fuzzy rules produce modified voltage errors. The IT2 Fuzzy system's rules are much more applicable to the Non-linear & Time-varying errors than the traditional T1 Fuzzy because the lower & upper membership functions (Voltage & Current Regulators) are implemented in an IT2 Fuzzy set. A 10 realistic bus bar system is used to validate the proposed method. Four scenarios that involve large load changes and variations of MW Generation from a PV Farm were studied and analyzed.

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