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A New Hybrid Intelligent Based Approach to Islanding Detection in Distributed Generation

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***Abstract*- This paper presents a new hybrid intelligent based approach for detecting islanding in distributed generation (DG). In this proposed method the passive and active techniques are combined to get a better reliability. So this hybrid method can secure the detection of islanding for different network topology and various operating conditions of synchronous machine based DG. Hence a better reliability is provided. This approach utilizes the artificial neural network (ANN) as a machine learning technology for processing and analyzing the large data sets provided from network simulations using PSCAD/EMTD software. The technique is tested on two typical distribution networks. The results obtained from one case study are compared with results of one of references to show the validity of the proposed method. The results of both studied cases indicate that the developed method can successfully detect islanding situations.**

***Index Terms*--Artificial Neural Network (ANN), Distributed Generation (DG), Islanding Detection.**

I. Introduction

Distributed generation may be defined as generating resources, other than central generating stations, that is placed close to load being served, usually at customer site. In fact, many utilities around the world already have a significant penetration of DG in their system. But there are many issues to be taken into account with the DG and one of the main issues is islanding.

Islanding operations of DG usually occur when power supply from the main utility is interrupted due to several reasons but the DG keeps supplying power into the distribution networks. In order to reduce the damages and dangers caused by islanding operation of DGs, the islanding formation should be detected quickly and DG should disconnect itself from utility network in short time [1,2]. Therefore the anti-islanding protection system of DG unit whose duty is preventing of the operation of these resources during network disconnection is one of the most important projects related to distributed resources.

There are many proposed techniques for detection of an island [3-8]. These techniques can be broadly classified into remote and local techniques. Local techniques can be further classified into active and passive techniques. Remote techniques for detection of islands are based on communication between the utility and the DGs. Although these techniques may have better reliability than local techniques, they are expensive to implement and hence uneconomical. Local techniques rely on the information and data at the DG site. Passive methods depend on measuring certain system parameters and do not interfere with the DG operation. Several passive techniques have been proposed which are based on monitoring voltage magnitude, rate of change of frequency, phase angle displacement, or impedance monitoring. If the threshold for permissible disturbance in these quantities is set to a low value, then nuisance tripping becomes an issue, and if the threshold is set too high, islanding may not be detected. In active methods, the DG interface control is designed to facilitate islanding detection by providing a positive feedback from either frequency or voltage . Since no islanding detection scheme can serve all DG source types equally, the method will normally be selected according to its nature (synchronous vs. static-inverter based) in order to maximize its efficiency and reliability. Anti-islanding protection for synchronous generators is a more challenging problem in comparison with the inverter-based generators. Options are limited for synchronous generators [6].

This paper introduces a new hybrid intelligent-based approach for detecting islanding in distributed generation (DG). This approach measures various parameters using a hybrid active - passive technique in order to secure the detection of islanding for any possible network topology, penetration level and operating condition of the synchronous machine-based DG. The proposed technique uses the artificial neural network (ANN) [9, 10] as machine learning method, to extract information from the data sets of these parameters after they are obtained via massive event analyses using network simulations. Simulation is carried out using PSCAD/EMTDC software. The technique is tested on two typical networks with multiple DG and the results indicate that this technique can successfully detect islanding operations. This technique is based on recognizing the patterns of the sensitivities of some parameters at target location to detect the situation of DG. The active method used here is the positive feedback of reactive power in addition to passive parameters which are voltage variation, rate of change of frequency, active power variation, total demand distortion and rate of change of frequency over active power variation.

In order to demonstrate the superiority of the method the results of the present study are compared with the results of Ref. [8] for same network. It is concluded that the accuracy of the proposed method is significantly improved and a shorter training time as well as detection time is justified. This is due to the fact that the number of measured passive parameters is reduced.

II. PROPOSED METHOD

In general two active methods are used for synchronous machine-based DGs which are active power and reactive power anti islanding schemes [11]. In both schemes the positive feedback is provided to DG via reactive or active anti-islanding (AI) compensator. In active power approach, AI receives the variations of frequency as input and modifies the active power reference to the DG, whereas in reactive power approach, the AI compensator uses the variation of voltage magnitude to change the reactive power reference. Therefore both compensators provide positive feedback so that the voltage or frequency is further amplified and departing from limits. Therefore in this circumstance even for the worst case in which the variation of voltage or frequency is within specified limit during loss of grid, islanding can be detected. The schematic of DG equipped with AI schemes superimposed on the AVR and LFC loops, is shown in Fig.1.

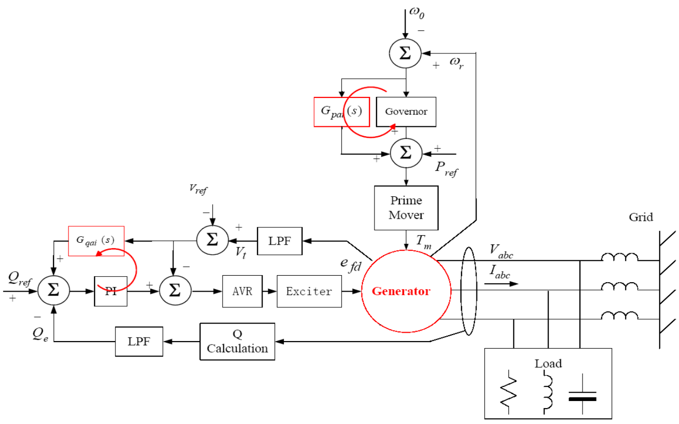

Fig.1 Diagram of synchronous generator with AI compensator

In the present paper to increase the accuracy of detection scheme, the reactive power- based active method is combined with the passive method. The used passive parameters are voltage, frequency, active and reactive power of DG and the total harmonic distortion of current.

III. PASSIVE AND ACTIVE METHODS

The concept of the passive technique is to measure the sensitivities of some parameters at a target location (the location at which the islanding detection is intended) to identify and classify any possible islanding operation. In the proposed technique the following indices are selected and defined at target location denoted by PCC in Fig.4.

$\Delta V/\Delta t$: rate of change of voltage under each event

$\Delta f/\Delta t$: rate of change of frequency under each event

$\Delta f/\Delta P$: rate of change of frequency over power under each event

$\Delta P/\Delta t$: rate of change of DG active power under each event

$\Delta Q/\Delta t$: rate of change of DG reactive power under each event

TDD: total harmonic distortion of current under each event

As mentioned before, the concept of active technique is based on incorporating the AI compensator in the control loops of synchronous generator having the appropriate design. The compensator consists of a washout filter and a proportional gain. The filter is designed in such a way to react only to transients of voltage or frequency but not to any steady state error. The requirements for open-loop gains are as follows [11].

(a) When the grid is connected, the open loop gain should be less than 0db at all frequencies, so its effect is nominal in this case.

(b) When the grid is disconnected, the gain must be greater than 0db to ensure unstable system, hence islanding condition is detected. To meet the above criteria, the compensator can have the transfer function illustrated in Fig.2.

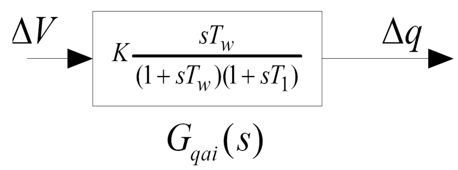

Fig. 2 Transfer function of AI compensator

It consists of a washout filter with corner frequency $1/T_W$, gain K and low pass filter with corner frequency$1/T_1$. The washout acts as a high pass filter so a signal with frequency higher than $1/T_W$ will pass unchanged. A signal with frequency lower than $1/T_W$ is attenuated. Therefore the effects of compensator on steady state regulation are minimized. For the selection of gain, a compromise to be made between a high gain for fast detection and a low gain to have no adverse effect on the normal operation of DG in case of grid-connected. By adding this function to automatic voltage regulator loop (AVR) together with PI controller, the compensator loop is completed. The principles operation and design procedure of this active scheme are fully described in [11]. According to investigations were carried out in this reference, the parameters of the compensator are defined as follows.

$$G_{qai}(s) = \frac{\Delta q}{\Delta V} = \frac{2.41s}{(1+0.048s)(1+0.016s)}$$

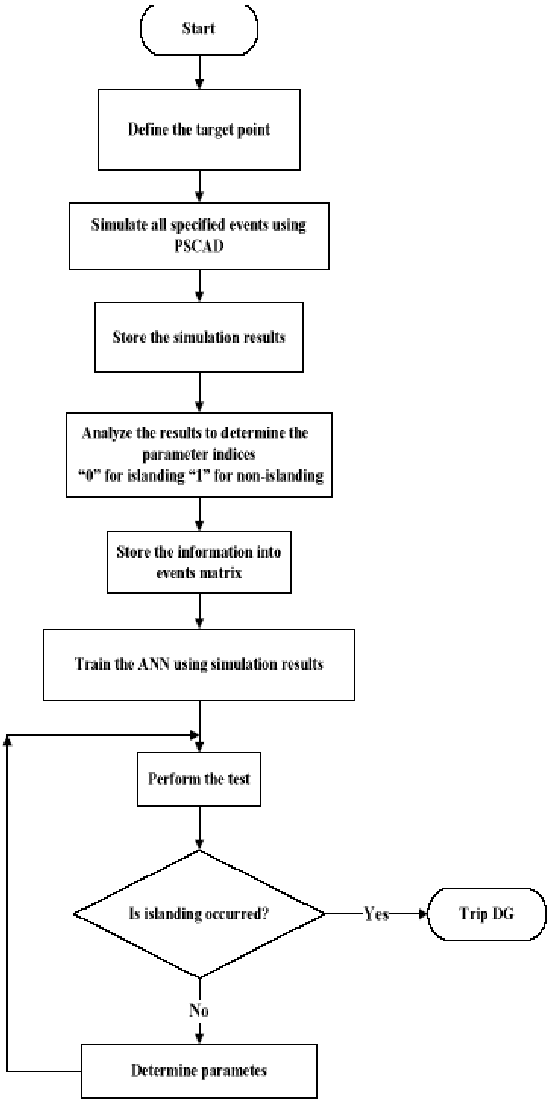

Fig3. Flow chart of the proposed method

IV. Implementation of the Proposed Method

The proposed method is a hybrid approach based on recognition of the sensitivities of 6 indices at the target point using ANN along with the operation of AI compensator which is embedded in the AVR control loop. The flow chart of the algorithm is shown in Fig.3.

At first the target point at which the identification algorithm to be implemented is specified and then various sets of events are defined. These sets of events can be provided by faults and switching actions under different loading conditions, namely light loading, normal loading and heavy loading. For each set of event the network simulation is performed using PSCAD/EMTDC software and the parameter indices are determined. When the simulation is accomplished for all prescribed events the obtained parameter indices together with corresponding islanding detection index are stored in a matrix known as events matrix. This recent index is represented by 0 or 1, zero for non-islanding and 1 for islanding condition. At this stage the required analysis is done and the ANN training is performed using the simulation results. Finally the performance of the trained system is verified by application of some events. The resulting output parameter is compared with the actual parameter so the misdetection error of test system can be found.

V. Numerical Examples

The proposed method is applied on two typical distribution systems. In the first case study the distribution network is same as Ref.[8], but in the second case study the induction motor load is also included to make the system more complex. To demonstrate the advantage of the proposed method, the obtained results are compared with the results of this reference. The algorithm is implemented on PCC bus associated with DG1. The considered events are: tripping circuit breakers, sudden change of load, occurrence of 3 phase fault, tripping DG2. Three load levels i.e. light, normal and heavy load conditions are considered. Each set of event is represented by F_{ab}, in which "a" denotes loading conditions and "b" denotes various events.

A. Case Study I

The study distribution network is shown in Fig.4. The data of the network is given in [8].

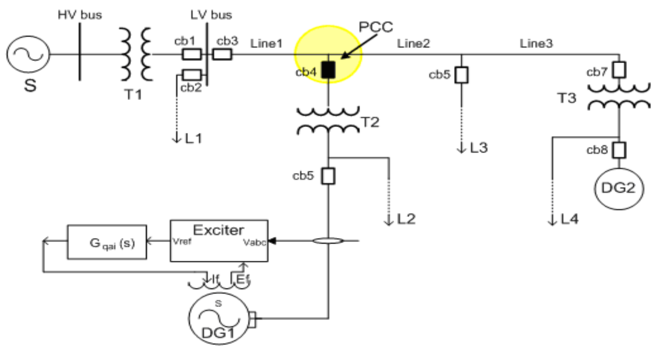

Fig4. Typical distribution system with RLC loads

Similar to this reference, 6 sets of events and 9 loading conditions have been considered. Events are: (1) tripping breakers1, 2 and 3 (2) three phase fault on HV bus (3) changing load at DG bus (4) tripping DG2. Therefore 54 (6 times 9) simulations have been carried out. The simulation results, which are the parameters indices at the target point under each event, are stored in a matrix. These results are transferred to ANN algorithm in Nero Solution environment.

From the total of 54 events 27 events (half) are used for training and the rest are used for testing. Results of the 27 sample testing events and the resulting parameter indices and the output of algorithm are summarized in Table1.

TABLE I
RESULTS OBTAINED FROM ANN ALGORITHM IN CASE STUDY I

Fault	TDD	$\Delta Q_{pcc}/\Delta t$	$\Delta P_{pcc}/\Delta t$	$\Delta V_{rms}/\Delta t$	$\Delta f/\Delta t$	$\Delta f/\Delta P_{pcc}$	Actual	output	Test1	ERROR
F14	0.8239	-3.4676	-3.8092	1.9319	0.003	-0.0008	1	1	1.03303	0.03303
F15	0.3284	-3.4111	-3.2623	1.2527	0.056	-0.0172	1	1	1.068444	0.06844
F18	-0.0044	1.1911	-0.3479	0.1708	-3.6207	0.4079	0	1	0.664612	0.66461
F110	0.0087	-1.2529	0.4415	0.3894	-3.6787	-0.3323	0	0	-0.12495	0.124951
F31	-0.0202	1.3433	3.1403	1.0604	2.834	0.9025	1	1	1.127084	0.12708
F33	-0.0131	1.6906	0.874	1.6346	2.8265	3.234	1	0	0.649058	0.350942
F35	0.4456	-0.6756	-1.565	1.0656	5.7535	-3.6764	1	1	1.147643	0.14764
F36	0.0017	0.0715	-0.3257	-0.0054	0.0022	-0.0068	0	0	-0.01576	0.015757
F37	0.0243	-0.3558	0.1902	-0.0073	0.004	0.021	0	0	0.048821	0.04882
F 39	-0.0204	-0.0699	-0.3558	-0.0784	1.5734	-0.4221	0	0	-0.09227	0.092266
F410	-0.003	-0.1305	-0.1019	-0.0134	-1.6535	1.0459	0	0	0.038382	0.03838
F510	-0.0019	0.1375	-0.6829	0.1399	2.6005	-0.808	0	0	0.097745	0.09775
F65	0.1449	-1.3095	-1.4645	1.9459	-2.8908	1.9739	1	0	0.78265	0.21735
F68	0.0028	0.0573	0.3096	-0.3896	-0.9107	-2.9415	0	0	0.009731	0.00973
F77	0.0093	0.0488	0.4229	-0.2721	-0.0057	-0.0135	0	0	0.186067	0.18607
F78	0.0028	0.1536	0.0886	0.0105	-0.9003	-0.1614	0	0	0.073754	0.07375
F710	-0.003	-0.1305	-0.1019	-0.0134	-0.8011	1.8616	0	0	-0.08537	0.085367
F81	0.0061	-0.32	2.0651	-2.1459	-2.85	-1.3801	1	1	1.007161	0.00716
F82	0.0026	0.2827	-0.4485	-0.2468	0.0001	-0.0002	0	0	0.184465	0.18447
F83	0.0229	0.4891	1.3862	-3.4739	-2.8472	-2.0539	1	1	0.977185	0.022815
F84	0.0617	-0.4147	-2.6455	2.3571	-0.1039	0.0393	1	1	1.052606	0.05261
F87	0.0058	-0.0701	0.5734	-0.2891	0.05	0.0872	0	0	0.043183	0.04318
F91	-0.0142	1.3284	2.382	5.6441	0.4772	0.2004	1	1	0.857288	0.142712
F92	0.0003	0.1168	-0.3661	0.0137	0.0185	-0.0505	0	0	0.019921	0.01992
F94	0.2036	-2.2315	-1.962	-3.4826	0.1076	-0.0548	1	1	0.84516	0.15484
F96	-0.0004	0.0759	-0.3592	0.0398	-0.0075	0.0208	0	0	0.016519	0.01652
F99	-0.0235	-0.2335	-0.2997	-0.8636	0.107	-0.357	0	0	0.015876	0.01588

By comparing the values of two columns of this table entitled "actual" and "output" it is found that in 3 events (F18, F33, F65) false detection occurred. The rate of false detection for this studied case is 11.1% (3 cases amongst 27 events). The results of sensitivity analysis obtained by this algorithm are also shown in Fig.6. This figure illustrates that how the measured parameters can affect the response of algorithm. It can be seen that the effect of rate of change of reactive power is more pronounced. This is due to the employment of active technique in the islanding detection algorithm. The effect of rate of change of frequency over power is so small it may be eliminated from measured parameters without losing accuracy.

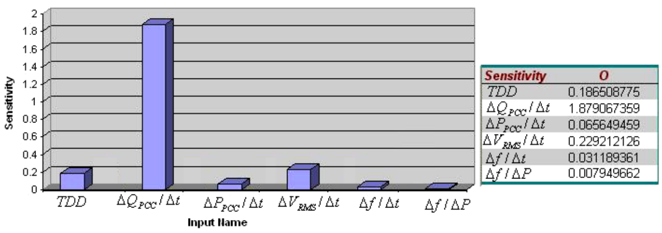

Fig. 6 The sensitivity analysis of measured parameters for case study I

B. *Case Study II*

The second study system is shown in Fig. 5 This network is same as the previous one except that an induction motor load is included.

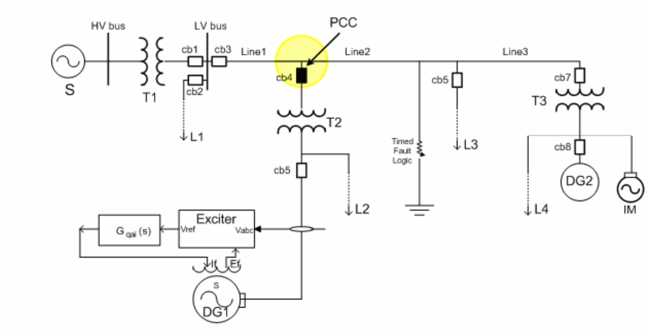

Fig. 5 Typical distribution system with RLC and Induction motor loads

In this case also more events have been considered. The number of events increased to 11 but the 9 loading conditions remain the same.

Events are: (1) tripping each of 8 breakers (2) three phase fault on HV bus (3) tripping the largest load (4) starting induction motor. Therefore 99 (11 times 9) simulations have been carried out. The simulation results, which are the parameters indices at the target point under each event, are stored in a matrix. From the total of 99 events 54 events are used for training and the rest are used for testing. Results of the 45 sample testing events and the resulting parameter indices and the output of algorithm are summarized in Table2.

TABLE II
RESULTS OBTAINED FROM ANN ALGORITHM IN CASE STUDY II

Fault	TDD	$\Delta Q_{pcc}/\Delta t$	$\Delta P_{pcc}/\Delta t$	$\Delta V_{rms}/\Delta t$	$\Delta f/\Delta t$	$\Delta f/\Delta P_{pcc}$	Actual	OUTPUT	TEST2	ERROR
F14	0.8239	-3.4676	-3.8092	1.9319	0.003	-0.0008	1	1	1.1592	0.1592
F15	0.3284	-3.4111	-3.2623	1.2527	0.056	-0.0172	1	1	1.02917	0.02917
F18	-0.0044	1.1911	-0.3479	0.1708	-3.6207	0.4079	0	1	0.562157	0.56216
F19	-0.0168	-0.5677	-0.7379	0.2972	0.0087	-0.0118	0	0	0.045802	0.0458
F110	0.0087	-1.2529	0.4415	0.3894	-3.6787	-0.3323	0	0	-0.13404	0.134036
F22	-0.0008	-0.2815	-0.5179	0.0021	0.011	-0.0212	0	0	0.008221	0.00822
F26	-0.0002	-0.2684	-0.481	0.002	0.005	-0.0104	0	0	0.004348	0.00435
F27	0.0092	0.2346	0.6085	0.0005	0.0024	-0.0039	0	0	0.181019	0.18102
F29	-0.0206	-0.1231	-0.5922	-0.0062	0.0228	-0.0385	0	0	-0.01818	0.018184
F31	-0.0202	1.3433	3.1403	1.0604	2.834	0.9025	1	0	1.35441	0.35441
F33	-0.0131	1.6906	0.874	1.6346	2.8265	3.234	1	1	0.985607	0.014393
F35	0.4456	-0.6756	-1.565	1.0656	5.7535	-3.6764	1	1	1.160488	0.16049
F36	0.0017	0.0715	-0.3257	-0.0054	0.0022	-0.0068	0	0	0.032333	0.03233
F37	0.0243	-0.3558	0.1902	-0.0073	0.004	0.021	0	0	0.002192	0.00219
F 39	-0.0204	-0.0699	-0.3558	-0.0784	1.5734	-0.4221	0	0	-0.06487	0.064871
F 41	0.0406	0.6641	0.2717	-1.8061	-2.9709	-10.923	1	1	0.840759	0.159241
F43	0.0409	0.6633	0.2734	-1.8111	-2.9862	-10.923	1	0	0.76306	0.23694
F410	-0.003	-0.1305	-0.1019	-0.0134	-1.6535	1.0459	0	0	0.011799	0.0118
F51	0.0061	-0.32	2.0651	-2.1459	-2.85	-1.3801	1	1	0.981543	0.018457
F52	0.0026	0.2827	-0.4485	-0.2468	0.0006	-0.0013	0	0	0.088337	0.08834
F53	0.0229	0.4891	1.3862	-3.4739	-2.8472	-2.054	1	1	0.982151	0.017849
F57	0.0058	-0.0701	0.5734	-0.2891	0.011	0.0192	0	0	0.059893	0.05989
F59	-0.0221	-0.0834	-0.5028	0.6217	-2.4	0.7732	0	0	0.070123	0.07012
F510	-0.0019	0.1375	-0.6829	0.1399	2.6005	-0.808	0	0	0.010179	0.01018
F62	0.0003	0.1168	-0.3661	-0.0137	0.0185	-0.0505	0	0	0.004053	0.00405
F63	-0.0045	1.4974	0.1867	-6.0328	0.4757	2.5479	1	1	0.985186	0.014814
F65	0.1449	-1.3095	-1.4645	1.9459	-2.8908	1.9739	1	1	0.911504	0.088496
F67	0.0146	-0.2433	0.4332	-0.1757	-0.097	-0.2239	0	0	0.02541	0.02541
F68	0.0028	0.0573	0.3096	-0.3896	-0.9107	-2.9415	0	0	0.043481	0.04348
F71	0.0406	0.6641	0.2717	-1.8061	-2.9709	-10.936	1	1	0.912665	0.087335
F72	0.0001	-0.002	-0.0014	-0.0015	-0.0004	0.2857	0	0	0.014841	0.01484
F73	0.0409	0.6633	0.2734	-1.8111	-2.9862	-10.922	1	1	0.963067	0.036933
F77	0.0093	0.0488	0.4229	-0.2721	-0.0057	-0.0135	0	0	0.070114	0.07011
F78	0.0028	0.1536	0.0886	0.0105	-0.9003	-0.1614	0	0	0.075861	0.07586
F710	-0.003	-0.1305	-0.1019	-0.0134	-0.8011	1.8616	0	0	-0.00103	0.001034
F81	0.0061	-0.32	2.0651	-2.1459	-2.85	-1.3801	1	1	0.854335	0.145665
F82	0.0026	0.2827	-0.4485	-0.2468	0.0001	-0.0002	0	0	0.08836	0.08836
F83	0.0229	0.4891	1.3862	-3.4739	-2.8472	-2.0539	1	1	0.983509	0.016491
F84	0.0617	-0.4147	-2.6455	2.3571	-0.1039	0.0393	1	1	1.149485	0.14949
F87	0.0058	-0.0701	0.5734	-0.2891	0.05	0.0872	0	0	0.059996	0.06
F91	-0.0142	1.3284	2.382	5.6441	0.4772	0.2004	1	0	0.2758	0.7242
F92	0.0003	0.1168	-0.3661	0.0137	0.0185	-0.0505	0	0	0.162317	0.16232
F94	0.2036	-2.2315	-1.962	-3.4826	0.1076	-0.0548	1	1	0.868049	0.131951
F96	-0.0004	0.0759	-0.3592	0.0398	-0.0075	0.0208	0	0	0.033264	0.03326
F99	-0.0235	-0.2335	-0.2997	-0.8636	0.107	-0.357	0	0	-0.01176	0.011761

By comparing the values of two columns of this table entitled "actual" and "output" the false detected cases are cleared, which are 4 events (F31, F43, F91, F18). The rate of false detection for this studied case is 8.8% (4 cases amongst 45 events). The results of sensitivity analysis obtained by this algorithm are also shown in Fig. 7

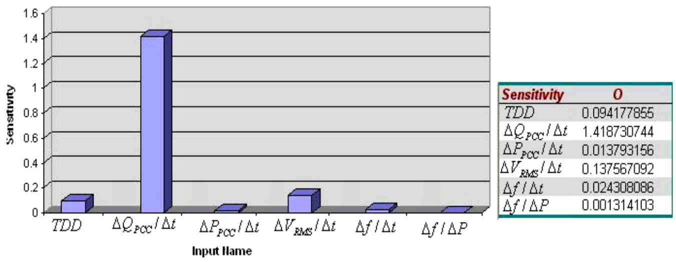

Fig. 7 The sensitivity analysis of measured parameters for case study II

It can be seen that in this case the effect of rate of change of reactive power is still high and the effect of rate of change of frequency over power is small.

VI. CONCLUSION

In the present paper a hybrid artificial neural network (ANN) based approach is proposed for islanding detection of distributed generation. In this approach the passive technique is combined with the active technique to increase the accuracy of the islanding detection method. As far as the active technique is concern, the positive feedback loop of AVR contributes to islanding detection by amplifying the rate of change of reactive power while having no adverse effects during normal operation of the network regarding the IEEE1547 standards. This has been shown using the sensitivity of measured parameters in both numerical examples. The results of first example in compare with Ref. [8] show that for the same network and also application of same events the rate of false detection improved from 16.67% to 11.1%. Furthermore in the proposed method the numbers of measured parameters are 6 while in the above reference 11 parameters are utilized. This is due to the incorporation of the active technique in the proposed method. The results of second example also demonstrate that although the network becomes more complex by incorporation of motor loading and increasing the number of events, the accuracy is preserved. The results corresponding to the sensitivities of measured indices imply that using the active technique with most effective parameter which is the variation of reactive power, along with passive technique, the accuracy of the detection algorithm is highly improved.

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