DYNAMIC SECURITY MONITORING AND PREVENTIVE CONTROL IN ISOLATED SYSTEMS WITH WIND POWER GENERATION USING ARTIFICIAL NEURAL NETWORKS

J. N. Fidalgo, J. A. Peças Lopes, Vladimiro Miranda
INESC - Instituto de Engenharia de Sistemas e Computadores
and DEEC/FEUP - Fac. de Engenharia da Universidade do Porto
P. República 93 - 4000 Porto, PORTUGAL
Fax: +351.2.2084172 email: jpl@obelix.fe.up.pt

Keywords: security, unit commitment and operational planing, neural networks

Abstract - This paper reports the application of a new artificial neural network (ANN) tool for dynamic secure managing of isolated systems with a large wind power penetration. In this research, ANNs are used not only for fast and accurate dynamic security assessment but also to move the system from insecure states into new secure ones. This procedure is based on power exchanging between diesel and wind generators, and also exploiting other combination of diesel units in operation. Computer simulations of the real power system of Lemnos (Greece) support the validity of the developed approach.

1. INTRODUCTION

In the last few years, we have been witnessing a growing interest in the use of renewable energy sources, motivated by environment concerns and economic appeals. Studies carried out in several countries have identified a high wind energy potential at various sites. In islands, there are particularly favorable conditions for wind power exploitation, due to an appropriate climate environment. Isolated systems of this nature supply energy to 3 to 5% of European Union population, and are a major supply source on many developing countries.

In isolated systems, conventional production is mainly provided by Diesel generators, with high production costs resulting from high fuel prices and from the costs of fuel transportation. Therefore, power production costs can be considerably reduced if wind power production is increased. However, power systems that include wind generation are exposed to fast wind power changes and to very high wind speeds, which may provoke a sudden loss of wind generator production. These production changes must be fast and efficiently compensated by the Diesel generators; otherwise, large voltage and frequency variations, or even the collapse of the system, may result.

To avoid these problems, a very conservative policy of operation dispatch is usually adopted by local utilities, leading to increased spinning reserve (SR) requirements, to under exploitation of wind power production and to higher production costs.

Therefore, to increase wind power production in isolated systems, without compromising dynamic security issues, new advanced control systems and tools must be installed and integrated with local SCADA (Supervisory Control and Data Acquisition) which provides data from the network. This data concerns wind speed, power outputs of renewable and conventional production units, load consumption levels, temperature, etc.

Such a prototype of control system has been developed and integrated within an existing SCADA on the Greek island of Lemnos, within the framework of JOULE II European Union research and development program. The control system is operating since January 1995 in the island and an evaluation stage is presently going on.

This advanced control system suggests an operating strategy for the upcoming hours by displaying to the system operators the start and stop schedule of the diesel machines and wind generators. These suggestions are performed by a "unit commitment and dispatch module", incorporating results from short time load and wind forecasts, and based on minimization of global production costs.

The control system also includes dynamic security assessment tasks, such as: 1) fast dynamic security classification of each generation schedule, calculated upon request of the "unit commitment and dispatch module" for a given set of wind power disturbances; 2) continuous on-line monitoring of dynamic security for current operating states.

This paper describes the approach developed for the tasks of security monitoring of the control system and presents recent new developments related with the definition of a set of preventive control actions. These measures are namely load redispatches and new unit commitment (UC) alternatives, for cases where insecurity is detected. These preventive control suggestions also take into account economic operation costs and are defined at two levels: a) immediate preventive control (if possible); and b) short term prospective control, involving some interaction with the "unit commitment and dispatch module".

In this project, ANN are an essential piece of the approach now described. Not only do they perform consistently better than traditional statistical methods in the dynamic security pattern classification [2], but they also provide means for evaluating the degree of security. Moreover, they provide simple and effective mechanisms of computing the derivatives of a security index with respect to the control variables. Such ability allows the

application of gradient based methods. In this paper, we show how these methods can be used to escape from dynamic insecure states and achieve new secure ones, keeping track of the economic issues related.

A complete description of the project and its modules, such as "wind power and load prediction", "unit commitment and dispatch" and "security assessment and monitoring" may be found in [1].

2. PREVIOUS WORK

Considerably activity has been devoted in the last years to the application of ANN for dynamic security assessment. The first attempts in this field were led by Sobajic and Pao [3] that have designed a multilayer network for fast evaluation of critical clearing time. Latter Kumar *et al.* [4] described in a general way the requirements needed by ANN to evaluate dynamic security in large power systems. Djukanovic *et al.* [5] developed the approach of Sobajic [3] and presented a new ANN approach for the determination of load shedding amount that assures transient stability. More recently Quin Zhou [6] started exploiting ANN with the concept of vulnerability. A good description of the application of ANN techniques in power systems can be found in [7].

Recently the authors of this paper presented a new ANN based method for transient stability assessment and preventive control [8, 9] . This approach evaluates the transient stability degree, on the basis of the emulation of the transient energy margin, and defines preventive control measures through a hybrid ANN-optimization method that solves an economic dispatch with transient stability constraints using a minimal incremental operation cost strategy [8, 9].

Although a lot of research has been reported in this field, the number of successful real case applications is still rather small. In this paper, we describe a real case application of ANN to the dynamic security evaluation problem of a medium size isolated network.

The developed methodology is also an extension of the method previously described in [8, 9] and includes the enlargement of the system stable domain by including new different UC alternatives. This means that when an insecure OP is detected by the "security monitoring module", a preventive control algorithm looks for secure OPs, not only on the basis of power exchanges among generators, but also exploiting new feasible UC alternatives, namely suggested or resulting from the interaction with the "unit commitment and dispatch module".

3. ANN FOR DYNAMIC SECURITY EVALUATION

On-line analysis of system behavior for specified wind power disturbances is practically impossible using conventional tools. Therefore ANNs were used for on-line and accurate evaluation of system stability degree relatively to pre-selected severe wind power disturbances.

The global approach involves the following major steps:

1 - Generation of a representative set of operating points and selection of the ANN inputs;
2 - Design an ANN able to evaluate on-line the system dynamic security degree.
3 - Definition of preventive actions, exploiting some ANN capabilities, that push system into security.

Each operating point of the set referred in step 1 is characterized by a large number of system variables. However, ANN inputs must be characterized by the following properties:

a) adequately characterize the system state; at the same time, this set should be small enough to avoid a large number of ANN parameters;
b) be independent among them;
c) include a subset of monitorable and controllable variables so that it might be possible to exercise control actions in the system.

Moreover, these variables should be directly obtained from the SCADA data base to ease the monitoring and control procedures. Most of these variables are directly related with the wind power production levels and Diesel machines UC and dispatch.

3.1 . The Lemnos Study Case

The electric power system of Lemnos comprises one diesel power station (DPS), two wind parks (WP), and two (2*250 kW) photovoltaic plants (PV). The DPS comprises five Diesel units (2*1.2 MW and 3*2.7 MW; one of the 2.7 MW units is only used when one of the others is in maintenance). The two WPs have the following nominal capacities:

WP1 : 8*55 kW + 7*100 kW = 1.14 MW;
WP2 : 12*225 kW = 2.7 MW.

Each of the two PVs is rated at 250 kW. The relative small size of PVs and the particularly fast response of their control systems lead to their influence on the system dynamic behavior being minor. A full description of the

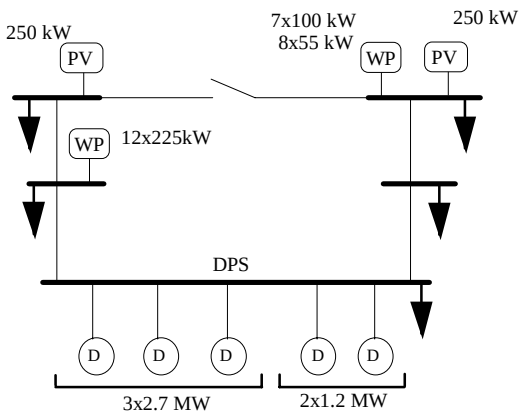

Fig. 1 - Single line diagram of Lemnos power system

Lemnos system can be found in [1]. Figure 1 presents a simplified version of this network, where D represents a single Diesel unit.

3.2 Selection of the System Security Index

Isolated power systems that include wind power production are particularly sensitive to sudden wind changes. If the frequency deviation caused by wind disturbances is greater than a certain threshold, protective devices, such as frequency relays, are set to operate performing the disconnection of the wind parks or load shedding defined by the local utility.

Therefore the maximum absolute frequency deviation (Δf) was chosen as the index that characterizes system dynamic behavior. In this study, the system was considered secure if $\Delta f<0.7$ Hz and insecure otherwise.

The evaluation of Δf index, for a given wind power disturbance, as the one presented in figure 2, can be performed using a full dynamic security study. This evaluation needs the numerical solution of the differential equations of the system adopting a complete representation of its components (asynchronous and synchronous generators with governor and voltage regulating devices), which would demand an unacceptable large computational effort. Therefore, an ANN based approach was used. The output of the ANN to be designed is the Δf value of the system when the pre-selected wind power disturbance, presented in figure 2, occurs.

3.3 Details on ANN Development

The training set was generated by varying the total load (PL), the total wind power (Pw) and the wind margin (WM). The WM is defined as the ratio of the diesel spinning reserve to the total wind power. This set was built to represent a large spectrum of possible operating points, not only for the present conditions but also for some expected increase in load consumption or wind production in the near future. This will avoid the need of re-training the ANN continuously.

This data set comprises respectively 1177 patterns used for learning purposes and 588 for test. Each data set operating point is characterized by a Δf value, obtained from a complete dynamic simulation performed during several seconds after simulating the occurrence of the wind perturbation described in figure 2.

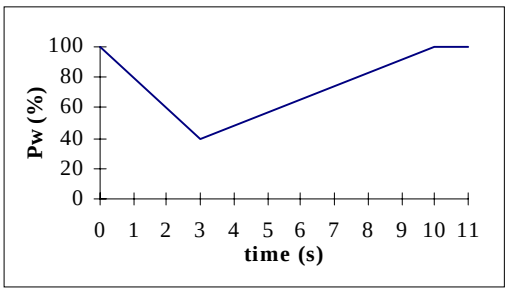

Fig. 2 - Wind power disturbance

This phase is developed off-line and involves a large computational effort. In very large systems this may become the bottleneck of the application of this approach. However the learning set dimension can be kept reduced if engineering judgment is previously used to identify some particular operating conditions to be included in the learning set generation procedure [10]. For example, operating strategies for peak load, light-load diagram periods or certain periods of the year (due to availability of energy resources) can be used.

A measure F of separability was used to select the most representative system variables [2]. The first selected variables where: PL, Pdn, Pw, WM, WP, Pd1 and Pd2, with Pdi representing the power produced by diesel units of type i. The wind penetration (WP) is defined as the ratio between Pw and PL.

An ANN (called ANN3 in figure 3) was then trained using as inputs this set of variables and as desired output the Δf index. In this work, we have used feedforward ANN's and the Adaptive Backpropagation (ABP) training algorithm [11]. The ABP uses an individual adaptive learning rate for each weight, which provides a much faster learning process. The stop training criterion was based in the well known cross validation principle, which fights against overfitting. Despite the good approximation of ANN3 output to the target values Δf, we could not use this ANN for control purposes. Notice there are non-independent variables on ANN3 input.

If ANN inputs are independent and controllable, then it is possible to control the effects in Δf (ANN output) of any changes in those inputs. Besides they should be able to represent accuratly the usual operating scenarios.

From the initial selected variables it was possible to identify a reduced set, characterized by the property of independency among them, able to represent the system (defining the new ANN inputs):

- Actual or forecasted load of the system PL;
- Actual or forecasted wind power production Pw;
- Nominal capacity of Diesel units in operation (or scheduled) Pdn.

This set of variables fulfills the required assortment of properties. Note that variable Pdn is directly related to the UC definition. Since there is a biunique relation between the Pdn values and the set of diesel generators in operation, Pdn will be the "perfect" candidate as a control variable for the UC set-up.

There are 2 different types of diesel generators: G1 (1.2 MW) and G2 (2.7 MW). Table I represents the set of possible resulting combinations of machines in operation and corresponding nominal capacity of Diesel units in operation (Pdn).

Table I
Pdn values for all the combinations of diesel units in operation

nr. of G1	nr. of G2	Pdn (MW)
1	0	1.2
0	1	2.7
1	1	3.9
2	0	2.4
0	2	5.4
2	1	5.1
1	2	6.6
2	2	7.8

Variables WP, WM and Pd1 and Pd2 can be obtained from the set (PL, Pdn, Pw). Therefore, two ANNs were used for this purpose exploiting the available training set. The following steps summarize the ANN architecture assembling: 1- Building and training small ANN blocks, that establish relations among system variables with high discriminant power; 2- joining and fusing blocks and retraining the whole set as a single ANN. This approach lead to reduced training time and effort. The building blocks ANN1 to 3 and their dependencies are displayed in Fig. 3.

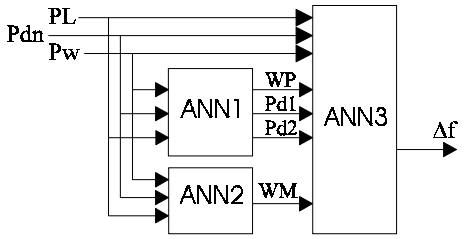

Fig. 3 - Building blocks of the ANN

Finaly, the basic blocks are compounded into a single ANN which is retrained. The final ANN architecture is composed of: 1st layer: 3 input units (PL, Pw and Pdn); 2nd layer: 8 units; 3rd layer: 4 units; 4th layer: 4 units; last layer: 1 output unit (Δf value).

This ANN was used to perform security classification tasks. The error obtained in the test set for the established Δf limit (0.7 Hz) was 0.68% (4 misclassifications in 588 tested patterns). In order to study the robustness of the ANN classification, we repeated the same classification

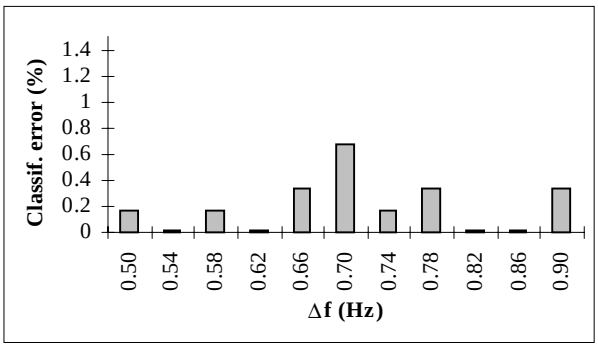

Fig. 4 - Classification error for several values of Δf limit

task with several different values for the Δf limit. This concern was motivated by the all possible settings of the protective underfrequency relays. Figure 4 shows that classification error remains nicely low, independently of the secure/insecure Δf threshold.

During the design stage, other Pattern Recognition Techniques, like the K Nearest Neighbors (KNN) method and Decision Trees (DT), obtained using an inference inductive procedure were also used for security classification purposes, as described in [2]. However, the results obtained with this ANN approach showed better performance, for the global classification error obtained, as described in table II.

Table II
Comparative performance results (threshold: Δf=0.7 Hz)

KNN	2.38%
DT	5.59%
ANN	0.68%

3.4 Dynamic Security Behavior

Although the ANN architecture is a little complex, it is a small tool (only three input variables) able to characterize system dynamic behavior for the specified perturbation.

Figures 5 and 6 display the behavior characteristics of the Lemnos system, coupling operation conditions (given by Pdn, Pw and PL) and security (given by Δf value). When looking at these figures , we can observe that there are regions in the curves where an increase in wind power production favors the system dynamic behavior (by decreasing Δf), which constitutes, at least at first sight, an unexpected result. This particular behavior can be explained by the analysis of the influence of Pw and the spinning reserve (SR) in system dynamic security. Notice that, for fixed PL and Pdn, a higher Pw (higher wind penetration) makes one expect a greater Δf, because the system becomes more vulnerable to wind changes. On the other hand, decreasing Pw implies a corresponding increase in the diesel power production (PD). If PD is close to Pdn, then the spinning reserve becomes small and the system loses its compensating capabilities and becomes specially sensitive even to small changes in Pw. These facts make it evident that there are two compromising terms (Pw and SR) whose settings require careful tuning.

Without this knowledge, one might be tempted to implement an algorithm that simply reduces the wind power production when a decreasing in Δf is desired; as we have just seen, that might result in an inappropriate approach.One might also expect that the higher the total capacity of diesel machines in operation, the greater the wind margin would become, and, therefore, the expected frequency deviations would decrease.

From observation of figures 5 and 6 one can see that this is not always true. We can observe the crossing of some

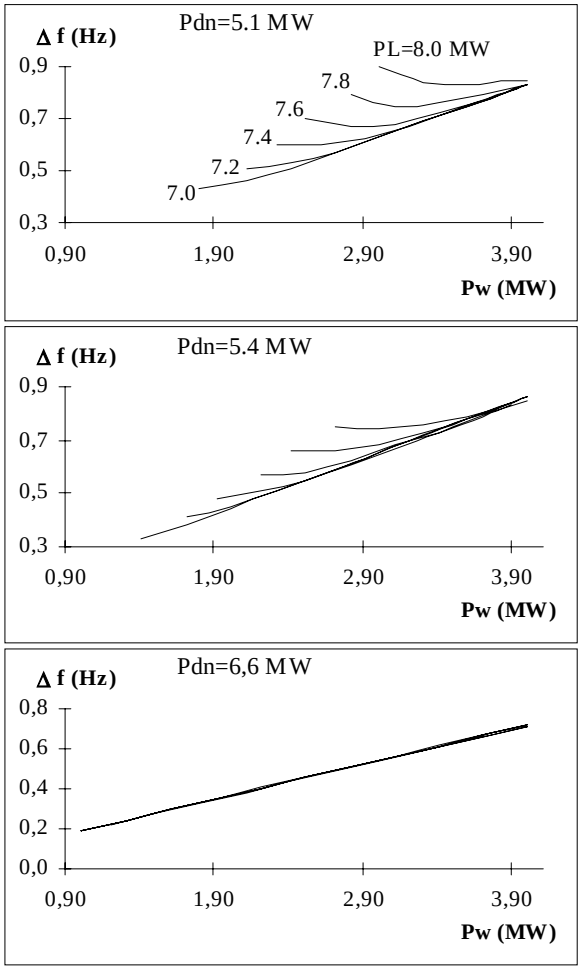

Fig. 5 - Family curves Δf=f(Pw) for several values of Pdn (each graphic) and PL (each curve). Pdn, Pw and PL in MW.

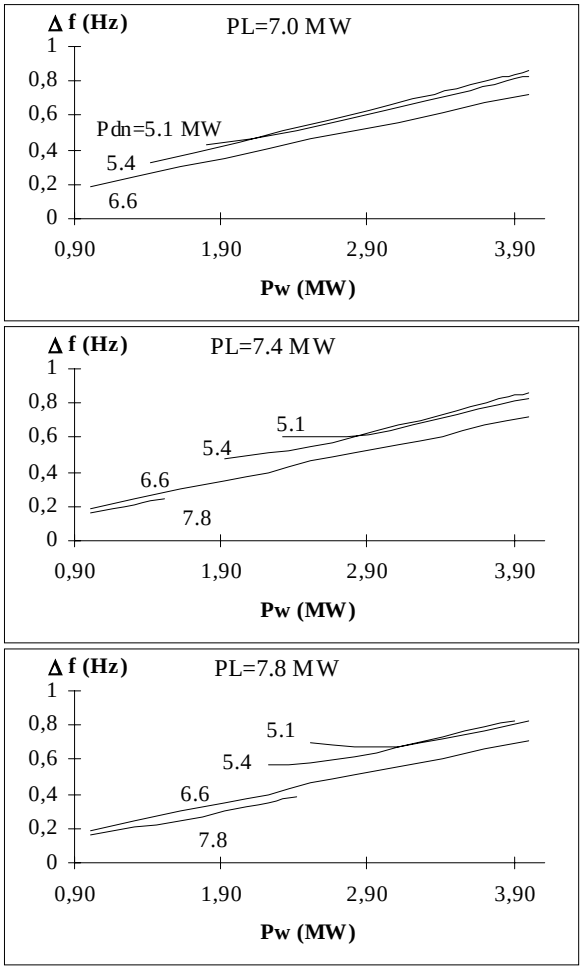

Fig. 6 - Curves Δf=f(Pw) for several Pdn values with PL kept constant. Pdn, PL and Pw in MW

curves (notice curves for Pdn=5.1 MW and Pdn=5.4 MW), which means that, in terms of dynamic security, the choice between these two values of Pdn must be made considering the values of PL and Pw.

From table I, we may conclude that the two types of machines (G1 and G2) have a different dynamic security behavior. For example, for Pdn=5.1 MW, we have 2 G1 type machines and one G2 machine and for Pdn=5.4 MW, we have 2 G2 machines. In spite of the higher value in the second case (providing a greater SR), the corresponding Δf value is not always smaller.

The knowledge gathered at this phase was used to define the type of possible preventive control strategies that are developed in next section.

4. PREVENTIVE CONTROL

Although the operating strategy of the system for the upcoming hours is defined to avoid insecurity, it may happen that, because of incorrect predictions of wind power and load, system may enter into an alert state. In this case, system operator should take preventive control actions. Having in mind that load shedding is an undesirable action, then for a given PL, we can change Pw and Pdn in order to cope with some target ANN output (Δf value).

Variable Pdn is changed by modifying the current Diesel unit-commitment. Pw is changed by disconnection-connection of individual wind generators at a given wind park. Of course, there is a set of constraints that must be satisfied when changing both Pdn or Pw:

a) Pdn is a discrete variable that can only take the values specified in Table I. Also, Pdn must be greater than PD (diesel power production);
b) Pw will not be increased when all available wind generators are already active;
c) When changing both Pdn or Pw, the algorithm must check if diesel technical limits of each diesel generator are not violated.

The preventive control algorithm developed (named LEMSEC) is basically composed by two procedures according to the type of suggestions provided: a) immediate actions (procedure PREV) that corresponds to connection /disconnection of wind turbines (eventually to be triggered by some automatic procedure) and b) short term actions (procedure PROS) corresponding to changes in Diesel UC and to be implemented under operator supervision.

If a potential insecure state is detected during system operation, then PREV procedure searches a new stable state by only changing Pw. In pseudo code, it could conceptually be described by:

```
Input (actual state)

/* define an immediate action to reach security */
if Δf>0.7 then
        repeat (if no constrain is violated)
                Δf(P_W^(n+1)) = Δf(P_W^(n)) + h · ∂Δf/∂P_W ;

                adjust h;
        until Δf<0.7

/* if state is "quite" secure then made it cheaper */
else if Δf<0.67 then
        while Pw<Pw_max  and not (0.68<Δf<0.7) do
            (if no constrain is violated)
            increase Pw;
```

where n is the iteration index and h is the gradient step.

Step h is adapted according system evolution trajectory: if $\partial\Delta f/\partial Pw$ keeps the same sign for several iterations, then h is increased; on the other hand, if its sign changes from one iteration to another or if a constrain is violated then h is decreased. Procedure PREV will stop if h becomes smaller than a given pre-established value or, of course, if $\Delta f<0.7$ Hz. Limit values 0.7, 0.67 and 0.68 are just example values. PREV algorithm accepts any reasonable values that system operator wants to experience.

Although Pw is a discrete variable, related with the connection/disconnection of wind generators, it can be tackled as a continuous variable during the iterative procedure and adjusted to the closest feasible Pw value afterwards.

The derivative of Δf with respect to Pw is evaluated through the ANN, as described in [8, 9]. New generated states are always feasible operating points, implicitly contained in the training set.

Procedure PROS is an extension of the algorithm developed for PREV applied to all feasible combinations of diesel machines (i.e., to all Pdn values suggested by the UC module). As this procedures tries to look into immediate future, the inputs of the ANN are based on wind and load forecasts. The load forecast sets directly the value of ANN input PL and the wind forecast sets Pw_{max} - maximum of wind power production. PROS searches then, a set of new combinations (Pdn, Pw) corresponding to secure/economical states.

Table III and figure 7 show results of the application of LEMSEC. Each state is characterized by PL, Pdn and Pw. Corresponding values of security index Δf and total hourly Fuel Consumption (FC) are also provided. Initial unstable state Si was transformed in a stable one f1 by PREV procedure. The other stable states f2..4 were provided by PROS procedure. It is clear that PREV was conceived to provide immediate actions in order to quickly reach security by only changing power production between diesel and wind generators.

Table III
Initial state and new state provided by LEMSEC (in this example, PL=7.0MW and Pw_{max}=4.0 MW)
f1 - PREV f2..4 - PROS

		PL (MW)	Pdn (MW)	Pw (MW)	Δf (Hz)	FC (g/h)
initial state	Si	7.0	5.1	3.507	0.734	819.5
New states	f1	7.0	5.1	3.328	0.697	861.5
	f2	7.0	5.4	3.208	0.693	925.2
	f3	7.0	6.6	3.746	0.675	782.2
	f4	7.0	7.8	3.984	0.622	703.1

The presented value of FC regards only operation costs and does not include start and stop costs of Diesel units. Procedures PROS wakes up the "UC and dispatch" module delivering it a set of secure/economical states choices and a dialog between the control procedure and the UC module starts.

Note that a trade off between security and operation costs may be established. The philosophy behind the global control system developed [1] requires that all information about units in service and dispatch corrections, obtained within a "security module", should be passed to the "UC and dispatch module", where they are combined with other constraints such as minimum up and down times, starting costs and other.

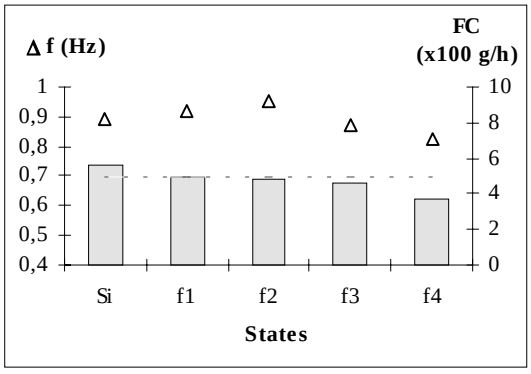

Fig. 7 - Security index Δf (bars) and fuel consumption FC (triangles) for initial (Si) and new states (f1..4) provided by LEMSEC

In brief, the preventive control algorithm performs:

a) definition of preventive control measures:
   - if insecurity is detected, the algorithm suggests appropriate measures (connection or disconnection of wind generators, in general), that might be taken immediately, to reach a stable state, and provides the new stable security index as well as related production costs;
b) prospective control:
   - based on the wind and load forecasts, the algorithm computes the dynamic security indexes and, in

association with the "UC and dispatach" module, defines a new set of possible secure states, showing its security indexes and its production costs.

5. CONCLUSIONS

This paper describes a successful case of application of ANN in the field of dynamic security assessment. The developed methodology provides:

- a new robust tool for accurate monitoring of dynamic stability;
- a better understanding of system dynamic behavior;
- an algorithm for the definition of preventive control actions;
- a start up for the definition of short term prospective control decisions.

Although this implementation was developed for a small size network, the results obtained are quite encouraging, and show that:

- The present approach constitutes an innovative insight in the field of dynamic security preventive control and provides a user-friendly tool to help system operators to manage in a secure way these kind of systems.
- Generalization of the developed technique is workable. The method previously described in [8,9] is here applied in another system, with a different security problem and distinct system representation.

The presented methodology was also successfully applied (on simulation) to a medium size power system (Madeira island). This network has a total installed capacity of 174 MVA, divided by one large Diesel power station (12 units of 4 different types), five hydro power plants and two large wind parks. Wind power penetration reaches 25% of total production during off-peak hours. For this case a neural network with an architecture (6, 8, 4, 4, 1) was used. The performance of this ANN was similar to the one obtained for Lemnos.

The described approach leads to higher penetration of renewable energies and contributes to assure a secure operation of isolated power systems with wind power production. Not only it provides the opportunity to operate an isolated system at lower costs, but also contributes to environment protection by lowering emissions from the Diesel stations.

6. ACKNOWLEDGMENTS

The authors want to thank the research team of the project JOU2-CT92-0053 for their contributions in the previous phases, related with discussions and specifications of the problem addressed in this paper and particularly National Technical University of Athens and PPC (Public Power Corporation of Greece) for the data provided.

7. REFERENCES

[1] E. Nogaret Et Al., "Development And Implementation Of An Advanced Control System For Medium Size Wind-Diesel Systems", Proc. European Wind Energy Conference, Thessaloniki, Greece, October 1994

[2] N. Hatziargyriou, S. Papathanassiou, J. A. Peças Lopes And V. Van Acker, “Pattern Recognition Versus Decision Tree Methods - A Case Study For Fast Dynamic Secutiry Assessment Of Autonomous Power Systems With A Large Penetration From Renewables”, Presented To The ISAP'94 Conference, Montpellier, France, September 5-9, 1994

[3] D. J. Sobajic And Y. H. Pao, "Artificial Neural-Net Based Security Assessment For Electric Power Systems", IEEE Trans. On PWRS, Vol. 4, Nr. 1, February 1989

[4] A. B. R. Kumar, A. Ipakchi, V. Brandwajn, M. El-Sharkawi and G. Cauley, "Neural Network For Dynamic Security Assessment Of Large-Scale Power Systems: Requirements Overview", Proc. 1st Int. Forum On App. Of Neural Networks To Power Systems, Seattle, USA, July 1991

[5] M. Djukanovic, D. J. Sobajic And Y. H. Pao, "Neural Net Based Determination Of Generator Shedding Requirements In Electric Power Systems", IEE Proc. C - Vol 139, Nr. 5, Sep 1992

[6] Quin Zhou, J. Davidson, A. Fouad, "Application of Artificial Neural Networks in Power System Security and Vulnerability Assessment", IEEE Trans. on PWRS, February 1994.

[7] Dagmar Niebur *et al*., "Artificial Neural Networks For Power Systems: A Literature Survey", Engineering Intelligent Systems, Vol. 1, No. 3, Dec 1993.

[8] J. N. Fidalgo, J. A. Peças Lopes, V. Miranda And L. B. Almeida, "Fast Assessment Of Transient Stability Margins By A Neural Network Approach", Proc. 11th PSCC, Avignon, France, Aug 1993

[9] V. Miranda, J.N. Fidalgo, J. A. Peças Lopes And L. B. Almeida, "Real Time Preventive Control Actions For Transient Stability Enhancement With A Hybrid Neural Network - Optimization Approach", IEEE Trans. On PWRS, Vol. 10, Nº 2, May 1995

[10] Y. Jacquemart, L. Wehenkel, T. Van Cutsem, P. Pruvot, "Statistical Approaches To Dynamic Security Assessment: The Data Base Generation Problem", To Appear In The Proceedings Of Sipower'95, IFAC Symposium On Control Of Power Plants And Power Systems, Caucun, 6-8 December, 1995, Mexico.

[11] F. M. Silva, L. B. Almeida, "Acceleration Techniques For The Backpropagation Algorithm", In "Neural Networks", L. B. Almeida And C. J. Wellekens (Eds.], Springer-Verlag, 1990

[12] D. E. Rumelheart *et. al*., "Learning Internal Representations By Error Propagation", In *Parallel Distributed Processing: Explorations In The Microstructure Of Cognition*,. Rumelheart And Maccleland Eds, Mit Press, Cambridge, Ma, USA, 1986.