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Connectionist Solutions for Energy Management Systems

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Abstract. In this paper a schematic survey on main tasks dealing with power system management has been accomplished. Each task has been defined and studied from a neural perspective. Moreover, a representative but non exhaustive analysis of recent reported works in the field is presented. Constitutive elements of a power system, such as generators, buses, lines, breakers, as well as most relevant magnitudes such as load, injection, active and reactive power flow, voltage and current, are introduced. The tasks which have been analyzed are Load Forecasting, Alarm Processing, Fault Diagnosis, State Estimation including Observability Analysis and Topology Assessment, Security Analysis, emphasizing Contingency and Transient Stability Analysis, and Operational Planning, including Expansion Planning, Unit Commitment and Economic Dispatch.

1. Introduction

Figure 1. (IEEE 14-bus standard network) is a schematic representation of an electric energy transmission system. Buses (B) represent real substations, lines (l) represent transmission lines, arrows (L) represent electric load of each substation, i.e., the electric energy exchanged between a substation and the external environment, triangles (T) represent transformers, and circles (G) represent Generators (thermal, hydro or nuclear units). A real system can comprise some hundreds of buses, lines and load connections, and tens of generators. In one such system the main goal is to maintain the equilibrium between consumed and generated energy. Since real generators, especially thermal units, have constraints such as minimum up-time and down-time, crew constraint, ramp rate limits, etc., this goal involves knowing the energy consumption with as anticipation and exactitude as possible (Load Forecasting task) and planning the distribution and activation of generators and loads in an optimal way (Power System Planning task). On the other hand, network security tasks have become a high priority subject due to the extreme social dependence from electric

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energy. In connection with security tasks, there are two large groups of operations: State Estimation, oriented to obtain the values that define the network state (voltages, currents, active and reactive power flows, breaker status); and Alarm Processing, Fault Diagnosis and Security Analysis, oriented to predict and, as soon as possible, solve faults and malfunctions in the system elements.

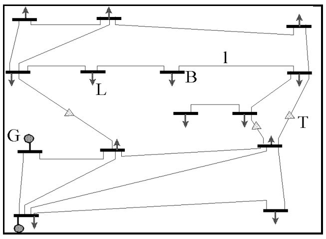

Figure 1: IEEE-14 standard network

These tasks present all or most of the following features: 1) Their solutions involve a high number of data such as bus voltage phasors, active and reactive power flows measured on both ends of a line, breaker status, transformer taps, etc. 2) Complex relationships exist among the variables implicated in each problem. 3) Massive information is difficult to handle by an operator. 4) It is difficult to find a numerical or algorithmical solution to every implicated problem, and if this solution is found, it presents a high computational cost. 5) They can not be described by means of a simple set of rules based on the knowledge of an expert. These characteristics and the social and economic importance of an efficient energy management make this tasks to be especially suitable for Artificial Neural Network (ANN) based techniques, and explain the existence of a high number of references about the topic.

In this paper the main operations involved in an Energy Management System (EMS) are analyzed from a neural solution perspective, the particular characteristics of each operation are brought to light and the most suitable neural structure is proposed in each case. Although many references are commented, an exhaustive bibliography revision exceeds our aim. A such survey, until 1992, can be found in [19], so we will attempt to report posterior works.

2. Load forecasting

The issue in load forecasting is to obtain future electric demand values by extrapolating past load consumption. The process can consider exogenous factors such as weather (temperature, cloudiness, wind-speed, humidity, rain), season, socio-economic conditions (working days or public festivities) and cultural conditions (special periods such as Christmas or Ramadan). Forecasting can be classified according to both the predicted quantity (peak load, integral load,

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hourly load) and the prediction interval (short term involving from hours to several weeks, long term involving years). Since electric energy can not be efficiently stored, to match production and demand is very important for an optimum power system management. Thus, in tasks as Operational Planning and Real-time Security Control, a good load forecast may be necessary. In the last years, the new deregulation and competition conditions in the energy market have given a new impulse to this task, and they have conditioned the forecasting period for adjusting it to the market operation periods.

The task presents serious difficulties among which the following can be emphasized: a) a high number of very different variables must be considered; b) very complex functions relate input and output variables; and c) the forecasting rules used in a determinate social, cultural and economic environment, can not be exported to other different environments.

Statistic approaches, such as time-series analysis and non-linear regression have been extensively used in this context, but the above mentioned difficulties make these methods inefficient without a previous intervention analysis, which involves serious flexibility and exportability limitations.

On the other hand, connectionist models or Artificial Neural Networks (ANN) are specially suited to deal with these difficulties because of their capability for learning from examples, short time reason at the recall phase and flexibility. Thus, the load forecasting task is the most frequently performed by ANN among all tasks involved in the power system management.

As a first approximation, feed-forward neural networks with backpropagation learning could be seen as the most adequate paradigm in this area because of two reasons: the problem can be explained in terms of obtaining an output variable (energy demand) as a function of a set of independent inputs, and a long historical data set is usually available. However, this paradigm has failed to obtain satisfactory solutions due to the following factors: a) The input variables are very different in nature, range and codification. This variability masks the role of each variable and limits the ANN learning capability. b) In a real case treating with an extended region, some exogenous variables can simultaneously present very different values at distant system points. c) Some variable can have direct or inverse effect over the load demand depending on each sub-zone characteristics. d) A particular public holiday will produce a very different effect on pre and post-day demands according to the day of the week it corresponds. e) The energy demand increases and the consumer habits change in time, so the useful size of the training set must be reduced and periodic training is necessary.

These limitations have motivated the use of alternative paradigms such as Genetic Algorithms (GA) [17] or statistic based pruned networks which may eliminate superfluous factors, Self Organizing Maps (SOM) by Kohonen to classify and divide the pattern set [4], Elman and Jordan recursive networks which incorporate temporal relations [28]. On the other hand, complex structures mixing various neural paradigms or neural and alternative methods (mainly Fuzzy Logic) [3] are more and more used.

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3. Power System Fault Detection and Diagnosis

When an event occurs in a power system, the operator must quickly know what has happened and what actions should be taken if necessary. Two tasks are involved in this goal, *Alarm Processing* and *Component Fault Diagnosis*. They share the requirement of short time response and a direct measurement input set, and are essentially different by the nature (either binary or analog) of these measurements.

Alarm Processing can be defined as the art of recognizing events, the state of power systems and the status of power system components from a large set of incoming signals and alarms [19]. Its goal is to assist the operator in isolating both the event and its causes. In an Alarm Processing System (APS) the input is a set of binary variables associated to circuit breaker state and relay data, and the output can be the detection of some of the following faults: single or multiple line fault, single or multiple bus fault, circuit breaker and relay malfunction and transformer fault. The main problems that an APS must deal with are: a) The large size of the real power system implies a high number of alarms, and an unmanageable number of these will be active during a system emergency. b) Major faults are infrequent, so the experience acquisition of a novice controller is very slow. c) Stringent response time constraints must be considered, so the reasoning time is very reduced. d) Both incomplete and corrupted information must be processed. e) The reception of equipment failure information (alarm activations) may be chronologically incorrect. f) Both explicit and implicit redundant information must be processed.

The most extended alarm processing method is based on priority levels. Each alarm is assigned a priority value, so that only one alarm, this one with the highest priority among active alarms, will be treated each time. On the other hand, rule-based systems present the drawback of their inability for handle both complex scenarios that are not encountered during knowledge acquisition and corrupted patterns. Finally, pattern recognition based methods present a long response time due to the high number of both alarms and possible faults.

ANN seem at first sight especially advantageous to face the pattern processing problems because of the following features: a) The training phase can be off-line and has not practical timing limitations. However, the recall phase is very quick. b) Certain neural paradigms (e.g. Radial Basis Functions) are able to both classify patterns and give additional information about the probability of falling in each class. c) ANN are very suited to cope with corrupted signal patterns. Most approaches face this task as a classification problem. Thus, in [13] a classification by hierarchic ANN structures is carried out while the input selection is accomplished by means of knowledge based methods. In [2] a Hybrid Learning System merging SOM and GA is introduced.

The *Fault Diagnosis* task deals with determining the state and quality of a monitored component from a limited set of analog signals dynamically obtained. The goal is to detect incipient faults and, consequently, to reduce repair costs, outage time and danger situations. A fault occurs when two or more conductor elements contact and its symptoms are related to abnormally high currents in

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a certain part of the system, voltage values falling out of permitted levels, and non balanced operation. Consequently, an early fault diagnosis can be obtained by continuously collecting and processing samples of these analog voltage and current quantities in the monitored element. Like in Alarm Processing, both pattern recognition and expert system based approaches are limited by the enormous quantity of information to be processed in a very short time, the noise inherent to field taken measurements and the difficulty for a knowledge systematization in this area.

Although Multilayer Perceptron with Backpropagation (MLP) has been initially proposed, it seems more advantageous to use complex neural structures dealing with a previous unsupervised clustering and a posterior supervised classification. In this sense, Counterpropagation (CPN), SOM, Radial Basis Function (RBF) or Progressive Learning Network (PLN) paradigms could be used. We will especially remark the transmission line fault diagnosis using neural networks reported in [23]. It uses thirty-three samples of three phase currents as inputs, and proposes a supervised clustering method, which can be divided into two stages: at the first one, input patterns are clustered following an unsupervised algorithm based on the Euclidean distance and a vigilance parameter r. At the second stage, non-homogeneous clusters are separated from homogeneous ones by a supervised algorithm, and they are clustered again. At the end, all clusters must be homogeneous and labelled with the associated faults. In the operation phase, each new pattern is assigned to the cluster with the nearest centroid.

4. State Estimation

Classical State Estimation calculates the most likely values of the power system state variables (voltage magnitude and phase angle at each bus), from a redundant set of active and reactive power flows and voltage magnitude measurements. The solution must minimize the sum $J(x)$ of quadratic weighted errors of all variables. Since a complete deployment of exact measurers is impracticable, the estimator module must face the following difficulties: a) many measurements are not available; b) all measurements are erroneous due to noisy instruments and measurement transmission channels; c) generation and reception of measurements do not necessarily occur in the same order; d) very erroneous pseudo-measurements must be considered; e) topological information can be erroneous or incomplete.

State Estimation can be accomplished by Hopfield networks by transforming $J(x)$ into an energy function [9]. Unfortunately, this approach is unfeasible even for very small power systems because of time requirements [11]. PLNs could be an alternative approach, but they are not able to handle topology changes. However, current numerical methods obtain very acceptable solutions, practically in real time. Besides, recent application of GPS technology to simultaneously obtain all the voltage and current phasor measurements allows for the simplification of the problem, because the equation system becomes

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linear. Consequently, neural approach to state estimation should be ruled out.

Anyway, even numerical methods need a minimum number of measurements that guarantees the system observability, and a correct topology information to develop the corresponding mathematical model of the system. Thus, a whole state estimation system must contain both *observability and topology assessment* modules in addition to the state estimator module.

Observability Analysis aims at determining whether the measurement set is sufficient to solve the state estimation problem. Otherwise, it must determine the most extensive observable regions. Basically, a system is observable if a power flow or power injection measurement can be associated to each bus of the system. This problem is optimally solved by algorithmic methods too.

On the other hand, current systems carry out both state estimation and bad data analysis considering the topological information as correct, so that an error in this one will produce an incorrect state configuration and erroneous detection of bad measurements. Consequently, identification of topological errors, or *Topological Assessment*, is actually needed in an Electrical Management System. In this problem, both in algorithmic and neural approaches the inputs are one or several variables among the following: line status (open or closed), active and reactive power flow measurements, normalized innovations, and normalized residuals. Line status variables have the drawback of including the erroneous information to be corrected. Power flow measurements present errors with a high standard deviation, which is a handicap for pattern separation and classification. Normalized innovations are obtained by means of a time series forecasting process, which loses reliability in situations of unexpected changes. Finally, normalized residuals are obtained from the estimation process, and may be caused both by topological errors and by bad measurements.

In [29], MLP, CPN and Functional Link Networks (FLN) are used, but the results are not practical in actual environments. In [25] a Constructive Artificial Neural Network (GMDH) is proposed using normalized innovations. In [10] a topology estimator using measurements directly supplied by SCADA (active and reactive power flows) is presented. It involves filtering data with a radial neuron layer, bus topology assessment with MLP networks, and a post-processing stage based on a set of simple rules.

5. Security analysis

Power system load continuously changes as response to successive connection and disconnection of consumer units. Although most individual changes are small in relation to the system size, serious conditions may appear when events such as faults on a transmission line or loss of a generator occur. In all cases, stable power system operations require a continuous match between energy input to the prime motor and electrical load in the system. If this match is not guaranteed, then the system frequency and voltage will deviate from normal, and a collapse situation could happen. The aim of security analysis equipment is to detect these deviations (security evaluation) and act to restore frequency

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and voltage to normal (security assessment) The changing market factors such as financial, regulatory and environmental conditions are forcing power systems to work near their security zone limits and any breach of security can have far reaching impact.

Currently, three stability conditions must be considered: *Steady State Stability* is the capability of the power system to remain stable and controllable with respect to small time dependent variations of the load resulting in frequency oscillation. *Transient Stability* is concerned with the ability of the system to remain stable after a disturbance prior to the action of governor control. In this situation, critical clearing time (CCT) evaluation plays an important role in the contingency solution process. If the clearing of a transient fault occurs in a sufficiently short time the system will remain stable. *Dynamic Security* is the ability of the power system to return to an acceptable steady state after the correcting actions are performed (end of transient stability period).

From a temporal perspective, Security Analysis can be divided in *Static Analysis* (SA) and *Dynamic Analysis* (DA). SA involves static variables and is oriented to steady state stability evaluation. If this stability is confirmed, SA studies the system stability in case of a probably critical event (contingency analysis). DA involves a continuous updating of the variables and is oriented to assessment analysis tasks during transient and dynamic stability periods.

The general flow chart of a static security analysis [7] can be described as follows: from State Estimation data one must evaluate the current operation point security. If the point is insecure, a corrective strategy must be proposed, otherwise, a contingency analysis must be carried out.

Contingency Analysis involves to select a set of feasible critical contingencies, to order it by means of severity criteria (contingency ranking), to evaluate each contingency effect, and to adopt corrective or preventive decisions. It can be applied both in planning and in operation mode. In planning, the goal is to examine the power system performance and the need for new transmission or generation expansion; in operation mode, the goal is to maintain a secure operating point [21]. The main objective is, from active and reactive power flows, total power demand, bus voltages, bus injection and other estimated variables, to obtain a Performance Index (PI). This index assists in estimating whether each considered contingency could generate an insecure or secure situation, and gives an idea on its severity. Several algorithmic methods have been developed to obtain this PI, among these the most used are minimum singular value of the system Jacobian matrix, modal analysis, eigenvalue and sensitivity, and P-V and Q-V methods, all of which require significant computation and, consequently, long screening time. Neural networks offer as an advantage the off-line training and quick on-line response. However, for real large power systems both the input number and the training sample number would be excessively high. On the other hand, topology changes will make the problem nearly unsolvable. Thus, most of reported applications consider some particular system elements (a subset of lines and buses) and a reduced contingency set. In [22] a Hopfield neural network is proposed for classifying

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contingencies. In [5] a MLP is applied to static security assessment. In [20] a SOM is applied to real-time contingency assessment. In [21], RBF are used for contingency analysis in planning studies.

The security analysis explicated above in a generic way can be particularized to *transmission line overload* and *bus voltage violations*. Transmission line overload is studied in [16] by means of a CPN, which is proposed to handle up to 44 contingencies as well as to perform the contingency ranking of a 71 bus, 145 line system. Bus voltage violation or voltage instability occurs when the power system is unable to maintain an acceptable voltage profile under an increasing load demand and/or configuration changes. In this situation voltage collapse will probably occur. In [14] a Layered Feed-forward Neural Network (LFNN) is proposed, which gives as outputs the voltage stability index for the overall system and the voltage-margins (deviation between the current voltage and the critical voltage values) for a selected set of load buses.

Summarizing, the main difficulty of the application of ANN to contingency analysis in general and voltage instability analysis in particular, is dealing with an enormous number of variables and contingencies. To avoid it, the following operations should be investigated: to select the load buses whose demand affects significantly the voltage stability limit, thus reducing the input number; to select the most meaningful contingencies; and to divide the power system into reduced zones.

In the Transient Stability problem, inputs can be mechanical rotor data, power generated during a fault, energy margin and topology information; and outputs can be CCT, Transient Stability Margins, future system load or a system vulnerability index. Almost all of neural approaches proposed in the last years involve using feed-forward networks with Backpropagation (BP) variants [6] [1]. In [18] a hybrid architecture combining conventional optimization and backpropagation is proposed. In [26] pattern recognition methods and backpropagation are used to assess transient stability and security transfer limits among interconnected systems. In [15] a fuzzy neural network is applied to real-time transient stability swing prediction. In this last reference, the criterion of instability is whether the difference between any two generator angles exceeds p radian in the first second after clearing time, and the output is a binary variable with 1 labelling unstable swing and 0 labelling stable swing.

6. Power system operational planning.

Power systems must operate in such a way that production costs are minimized over time and safety constraints are observed. Tasks involved in this objective can be globally named as *Operational Planning* and can be classified in very long term system planning (Expansion Planning) and relatively short term operation planning (Unit Commitment and Economic Load Dispatch).

From [8] *Expansion Planning* (EP) can be defined as follows: Given the network configuration for a certain year and the peak generation/demand for the next year along with other data such as network operation limits, costs,

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and investment constraints, the goal is planning *where, when and what* type of new equipment should be installed with the lowest cost. This task can be formulated as a multi-stage linear programming problem with continuous variables. In [8] the static transmission expansion planning is formulated as a mixed integer nonlinear programming problem and solved by means of a Simulated Annealing (SA) network.

Unit Commitment (UC) is the problem of determining when to start up and shut down units so that the total operating cost can be minimized [12]. This objective is subject to several constraints such as minimum up-time and down-time, crew constraint, ramp rate limits, generation constraints, load balances, must-run units, and spinning reserve constraints. Algorithmic and numeric methods have been extensively proposed in this area. Among these, merit order tables, dynamic programming, integer and mixed-programming, branch and bound, linear programming, and Lagrangian relaxation can be included. With respect to artificial intelligence, rule based methods and, more frequently, Fuzzy Logic and GA methods, working as modules of complex structures involving dynamic programming (DP) and SA have been reported. With respect to ANN, in [30] a hybrid Hopfield structure is proposed to handle both discrete and continuous restrictions, obtaining a combined Unit Commitment and Economic Dispatch solution. In [12] a feed-forward ANN is trained (initialized) by GA, and its output is post-processed by DP. In [24] SA is applied to improve the convergence of a GA, which is the main module.

Economic Dispatch (ED) is the process of determining the optimal allotment for each thermal unit so that the total fuel cost is minimized subject to the equality constraint on power balance and the inequality constraints on generation rate changes and line flows [19]. Classical optimization techniques such as the lambda-iteration, gradient, and dynamic programming have been used to deal with this problem. With respect to neural approaches, Hopfield neural networks have been extensively used. Conventional Hopfield networks applied to real cases present unacceptable time delays considering that the period of ED module activation must be between 3 and 5 minutes. In [27] a fast Hopfield variation is proposed by modifying the neuron activation function.

7. Summary

In this paper a schematic survey on main tasks dealing with power system management has been accomplished. Each task has been defined and studied from a neural perspective. Besides, a representative but non exhaustive analysis of reported works in the field is performed. The most important requirements of almost every operation involved in power system management are short-time response and handling a high number of erroneous measurements. On the other hand, too many unknown problematic situations often appear, which can not be solved with experience based methods. These features encourage to apply neural methods opposite to analytic and expert based ones. Some features of Neural Networks, such as off-line learning, rapid response in operation mode,

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corrupted data handling and generalization capabilities are emphasized. On the contrary, the high probability of topology changes to occur (each topology is in practice a different system), the excessive number of contingencies to be analyzed and the different nature and range of variables are negative factors for neural network approaches, favouring the use of analytical methods.

As a summary of the most adequate neural paradigm to be applied in each studied task, the following considerations can be made: In Load Forecasting a three stage structure can be recommended: at the first stage, a Self Organizing Map carries out a pattern classification, thus avoiding to use exogenous and qualitative variables; at the second stage, a supervised learning paradigm as a Multilayer Perceptron or a recursive Elman network, performs load forecasting from homogeneous load inputs; and at the third stage, a rule based method or a fuzzy logic method post-process the previous prediction in special cases. In Alarm Processing and Fault Diagnosis, because of the difficulty of large and erroneous input patterns, unsupervised preprocessing based on complex neural paradigms such as Counterpropagation or Progressive Learning Network could be recommended. In State Estimation operations, thanks to current computation capabilities, numeric methods are completely satisfactory for Observability Analysis and State Estimate modules. Only Topology Assessment appears as a possible neural application field. In Security Analysis a great variety of neural paradigms are applied. In this area an important research effort could be oriented to input feature and critical contingency selection. Finally, in Operational Planning, extended Hopfield networks and Simulated Annealing in collaboration with Dynamic Programming and other alternative techniques are applied.

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