Designing an Intelligent Decision Support System for Human-Centered Utility Management Automation Part 1: Structures, Problem Formulation, Solution Methodology

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Abstract: - This paper presents a Decision Support System (DSS) to aid the electric utility management automation system. A brief history of DSS application in power systems is presented. The importance and role of DSS and decision making in utility management automation are discussed. A power distribution system automation problem is stated, and a solution methodology, using problem decomposition, is formulated. Several training sets are derived mathematically from two numerical test sets, for DSS learning procedure. The paper includes discussions, structures, illustrations, numerical examples, and a complete reference citation for further reading.

Keywords—Decision Support, Utility Management Automation, Human-Centered Systems, Systems Design, Neural Networks, State Estimation, Power Distribution System, Decision Making, Computational Intelligence

1 Introduction

Most electric utilities have control centers for operating and management of their networks. Normally, a human operator acts as the main decision maker for the system. The control centers are designed to offer decision support to engineers and managers who must react quickly to system events and deal with the large volume of data that ensues. However, more effective system control can only be exercised, if the increased volume of data is matched by an increased capacity to interpret system conditions from the control room. This information quality enhancement task is done by a Decision Support System (DSS). A DSS is an Information system (IS) -based on Information Technology (IT) levers- which serves to decision maker, who is normally a human. This aspect can be called "Human-Centered Automation" [1,2,3,4].

One of the important aspects of decision support is classification. Classification is the basis of cognition. Each field of science starts with classifying its relative things in groups having certain or uncertain boundaries, namely "Taxonomy". A classifier system is a system, which determines the membership of its inputs to the certain classes.

A state estimator classifies (assigns) the condition of the system to one of the classes, here called "state". State of a system is the smallest set of linear independent variables, which can describe the system status in each moment of the time. State estimation is assigning a certain value (a state identification number) to each set of measured variables of the system. State estimation starts with measuring the input variables, which often includes imperfect, redundant or faulted values [5,6]. For a finite state system, the state estimator acts as a classifier. It performs a mapping from the measuring space to the space of system finite classes or states.

1.1 A Brief History of DSS in Power Systems

Decision support systems application in power system was introduced in 1960s and gradually was utilized in power system control centers. Dy Liaco et.al. and Burt et.al. introduced a system for interpreting SCADA alarms in power system [7,8] before the widespread interest in expert systems. However, it was only when expert system techniques were seen to provide the key to realize intelligent decision support, that the interest in this area became traditional. Matsumoto et. al. [9] were among the first to develop an expert system for application the power system domain.

Numerous papers have been published in power system state estimation as well, including: Schwepe et. al., [10] studied static state estimation methods, Dopazo et. al., [11] improved mathematical methods on power system state estimation, Simoes-Costa et. al., [12] introduced a robust numerical method for that, and Alemong et. al., [13] presented an estate estimator implemented in power system control center. Also in the field of power system intelligent estate estimators, researchers like Kim et. al., [14] and Santoso et. al., [15] presented interesting works.

In recent years, increasing effort for improving the performance of utility management and operation using decision support has been led to new methods and algorithms. Rivas [16] developed a real-time state estimation method for increasing transmission capacity. Lambert-Torres [17] presented a new approach decision support using rough sets (an information retrieval method). Also Hor et.al. [18] applied rough sets to knowledge extraction problems in distribution systems. DSS have had applications in new aspects of electric utilities either. For example, Liu [19] introduced decision support tools for trading in deregulated energy systems. Also, Damborg et.al. [20], Fischl et. al. [21], Shah and Shahidehpour [22], and Hubele et. al. [23], applied neural networks, sensor fusion, fuzzy logic, automated reasoning, and a generalized framework to this problem. Yang et. al. [24] used fuzzy Learning Vector Quantization (LVQ) networks for power transformer conditioning assessment. Strachan et.al. [25] presented a paper that applied knowledge management methods to power system protection problem. Chung and Fu [26] designed a voltage stability estimator. They utilized two sequential self-organizing hierarchical neural network (SHNN) models in their work. However, this paper does not seek to an exhaustive bibliography of relevant papers. Indeed, some excellent reviews of this field are in [27, 19, 29, 28, 9, 8].

2 Decision Support Systems

A DSS refers to a computerized information system, which assists decision making by combining data, analytical models and tools, and user-friendly software into an agent[†] that can support semi-structured or unstructured decision making[30]. DSS can support both managers and engineers with more reliable and precise information from the site. The higher quality information, will led to more efficient decisions [8].

The need to support for decision-makers is due to the cognitive limits, technical limits, economic limits, time limits, and competitive demands in engineering and managerial environment [32]. Various kinds of decision support can be provided, such as: user alert, problem recognition, problem solving, facilitating (extending the user's ability to process knowledge), stimulation, coordination, facilitating interactions, and so on. A good DSS should be simple, robust, easy-to-control, adaptive, complete on important issues, and easy to communicate with [30].

Fig.1 shows the location of a DSS in a power system control and management structure. [31]

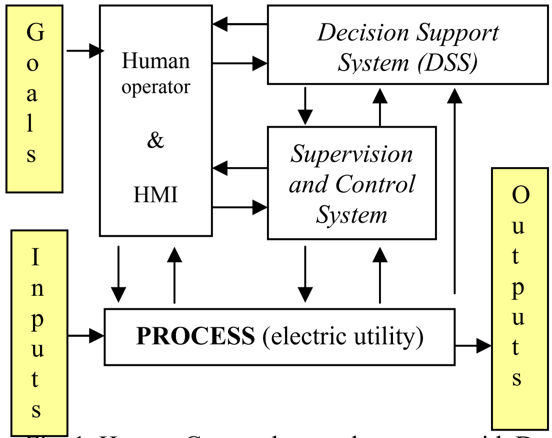

Fig. 1, Human-Centered control structure with Decision Support System, in an electric utility closed loop control system. The four upper boxes of the figure comprise the feedback loop.

Simon described the decision support function in 1977 as a four stage model [33]:

1. Intelligence[‡]: problem identification and information gathering.
2. Design: variant production for decisions on the basis of the intelligence.
3. Choice: decision selecting among the variants.
4. Implementation: final decision execution.

Anthony's taxonomy of control considers three levels of decision making: operational level, managerial level, and strategic level [34]. The Simon's model of decision making can be applied to each three levels of control levels.

In the operational level, the role of the first two stages of the Simon's model is clear. Oppositely, in managerial and strategic levels, the importance of the "choice" stage will be more focused. Especially in strategic decision making level, the most decision makings seem to be "to pronounce a judgment", rather than "to do a systematic decision making". This is due to more uncertainty of decision making, when we go from operational level toward the strategic level.

A good decision support agent improves the quality of information available to decision maker agent. In this case, more useful features are extracted from the raw data, which is prepared by the "intelligence" stage, in order to propose clearer and more proper variants in

[†] Agent may be a human, or software. In our specific project (Human-Centered Automation), the main decision maker is human, and the decision support is given to him/her by an intelligent neural network agent.

[‡] Here, the meaning of the word "Intelligence", necessarily is not equivalent to its in AI terminology as having generalization, abstraction, and learning ability.

"design" stage, and consequently easier selection of variants in the "choice" stage. So, a decision support agent may help the decision maker to transform an uncertain "judgment" to a clear, systematic, or even quantitative "decision making". Morse and Kimball wrote: "*Operations research is a scientific method of providing executive departments with a quantitative basis for decisions regarding operations under their control*"[35]. Nowadays, the method they described applies to decisions made by executives, individuals, and all sorts of groups [36,37].

3 Problem Statement

An electric energy utility has the duty of handing up the electrical energy to the end consumer. In recent years, numerous projects are implemented in various countries in the fields of Distribution Management System or DMS and Distribution Automation and Control or DAC. They include network planning, feeder reconfiguration, optimum capacitor placement, and integrated system protection and control. Their main goals are loss reduction, load balancing, reliability enhancement, service restoration, modifying voltage profile, etc.

3.1 Problem Decomposition

A DMS or DAC function can be decomposed into two sub-problems or sub-systems as shown in Fig. 2:

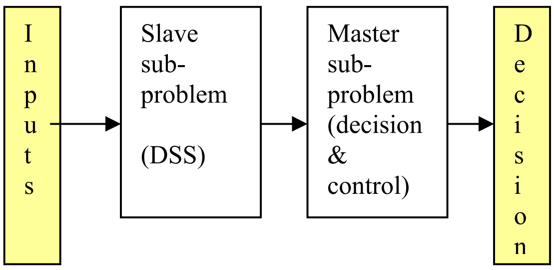

Fig. 2, Decision problem decomposition

- Master sub-problem: determining control or management strategies to reach to the specified objects (Decision and Control).
- Slave sub-problem: providing high quality and reasonably precise information for the master sub-system (Decision Support: state estimator or classifier).

3.2 The State Estimator DSS

In the power system theory it is shown that the power system variables vary in two de-coupled channels of P.θ and Q. $|V|$. Where P, Q, $|V|$ and θ are the real and imaginary powers, amplitude and phase of the voltage respectively [38]. Since, having P and Q is sufficient for studying the line loss, a vector including P and Q for each node of the network will indicate the states of the system for a loss reduction control scheme.

Fig. 3, Illustrating State Estimation Function

In this paper, an intelligent Decision Support System (the slave problem) has been introduced for distribution system control center. The presented DSS has been utilized in a distribution network control system (the master problem), which has been introduced in [39].

The stated DSS must be able to estimate load level of a zone (its state) on the basis of input data which are real and imaginary powers (P and Q), injected to that zone. It is evident that these states are dynamic and vary with the consumption. Having system states in every moment of the time can give a good understanding of loading status of the system.

Sensitivity analysis studies show that by increasing the injected real and imaginary power, load level sensitivity increases. Thus, higher load levels must be wider. According to this, four load levels having 40%, 25%, 20% and 15% sizes are taken by the names load level 1, load level 2, load level 3 and load level 4 (or state 1, state 2 ,...) respectively. Figure 3 shows this input/output mapping.

4 Preparing Training Sets for DSSs

Our intelligent decision support system is implemented as an Artificial Neural Network (ANN). In our problem, these DSSs (ANNs) act as classifiers (or estate estimators) for the load level of the electricity distribution system zones.

ANNs are known as firm-wares, because they are designed for a special purpose. In order to learn their duties, they need a training set. A training set is an experimental set of data, which indicates an input / output map that shows the behavior of the required classifier system. This methodology of design is known as a functional system design [40]. We have prepared many types of training sets in order to observe their effect on the learning process of the ANNs. In order to prepare more effective training sets, various data pre-processing were experienced on the decision space. Our aim was to test the DSS learning ability and the final designed system performance for the various types of training sets. In the preceding section we present the pre-processing performed on the decision space data, and also some observations on their nature. More discussions and the effect of the resulting training sets are presented in the Part 2 of this paper.

4.1 Decision Space Data Distribution

Comparing transfer functions of neurons in MLP and RBF neural networks shows that MLP network neurons (most sigmoid) are excited (high output) in the most of the space, but RBF network neurons (Gaussian or bell shape) is not excited in most of the space. Thus, it sounds that Gaussian (centered or bell shape) data distribution is more suitable for neural networks having Gaussian neurons (i.e. RBF neural networks).

An unsupervised algorithm, known as k-means clustering, does RBF middle layer training [41]. The algorithm assumes a class center (or cluster center) for every colony of data as a cluster. This class center is the central value (mean) of Gaussian transfer function. The class centers are found by an unsupervised method: estimating for the training set data centers. Thus, it can be said*: RBF neural network is a "Center Sensitive" or "Center Oriented" neural network.*

On the other hand, MLP neural network training is a supervised method. Boundaries of each class can be learned to the algorithm by learning a set of data -which is concentrated on the bounds of classes- or even uniformly distributed data. Clearly saying, *MLP neural network is a "Bound Sensitive" or "Bound Oriented" neural network.*

According to the above discussion, we consider two types of data distribution for training the neural networks.

1. Uniform data distribution (Fig. 4)
2. Centered or Gaussian data distribution (Fig. 5)

Both training sets consist of 80 data samples. Each data sample is a two dimensional vector of [P Q], which can be measured values of a utility line sections or buses, in normal condition:

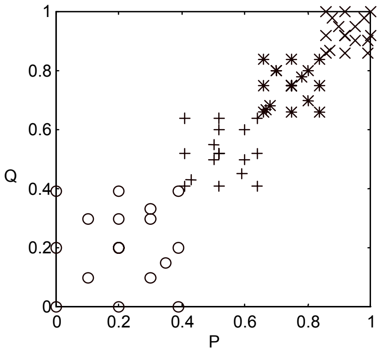

Fig. 4, Uniform data distribution classification space

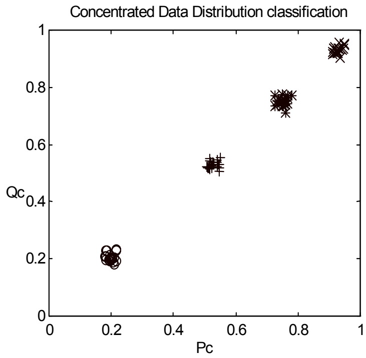

Fig. 5, Concentrated (Clustered) data distribution classification space

4.2 Space Equalization

Artificial neural networks are based on a mathematical model of biologic neuron. So, the classes, which their widths are almost equal, same to be learned easier. According to this, various exponential functions are studied. Then, relative deviation percentage (deviation in the widths of the classes) which has been calculated after implementing each of the functions, are sketched versus various bases of the maps in Fig. 6.

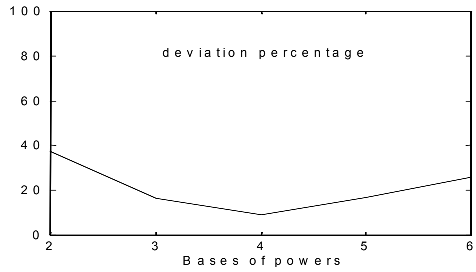

Fig. 6. Deviation percentage versus integer exponential bases

It can be seen in Fig. 5 that for P^4, deviation in the size of the states, is the least value. Thus, the P^4 and Q^4 functions have been selected, in order to equalize the size of classes. Result of implementing such a map with scaling coefficients on uniform and clustered distribution is shown in Fig.s 7 and 8.

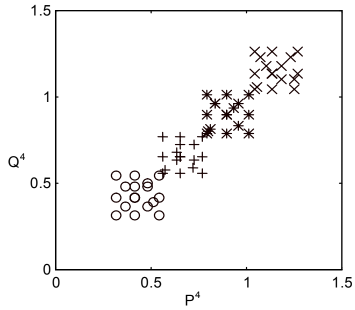

Fig. 7, Equalized uniform data distribution classification space

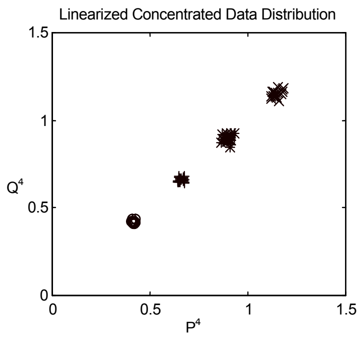

Fig. 8, Equalized concentrated data distribution classification space

4.3 Conformal Mapping

Radial basis nature of RBF neural networks suggests the idea of transforming the shape of classification space from rectangular form to circular form. Also, two-dimensionality of this space and imaginarity of one of space variables (reactive power) leads us to use complex analysis. Conformal mapping is a complex function, which maps a two dimensional zone to another two-dimensional zone in complex space. For performing this map, four candidates; exp(z) , (z-1)/(z+1) , (i-z)/(i+z), (cos(z)-1)/(cos(z)+1) -which all of them transfer a rectangular zone to a circular zone- are studied and compared [42]. Finally the f(z)=exp(z) complex function is selected. Fig.s, 9 and 10 show circular mapped classes for uniform and clustered data distributions, respectively.

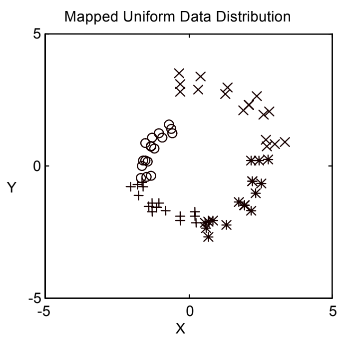

Fig. 9, Circular Uniform data distribution classification space

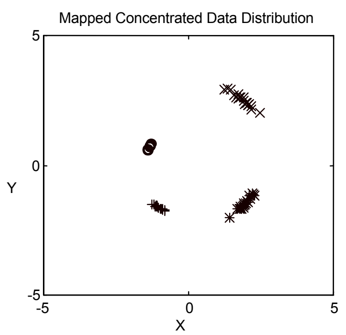

Fig. 10, Circular concentrated data distribution classification space

5 Conclusion

- A DSS can transform an uncertain "judgment" by the manager to a clear, systematic, or even quantitative "decision making", by providing higher quality data and processed information, in a Human-Centered management automation scheme.
- The proposed intelligent DSS support electric utility manager and operator in making decision, by providing more useful, correct information.
- The proposed intelligent DSS can reduce the risk of wrong decisions, by improving the quality and precision of data.
- The proposed intelligent DSS can reduce the risk of wrong decisions, by extracting more useful features and information from the raw measured data.
- The proposed intelligent DSS can reduce the decision making time and effort by providing processed information and gradually walking toward real-time applications.

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