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Computational Intelligence in Power systems

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Abstract — *A continuous and reliable supply of electricity is necessary for the functioning of today's modern and advanced society. Since the early to mid 1980s, most of the effort in power systems analysis has turned away from the methodology of formal mathematical modeling which came from the areas of operations research, control theory and numerical analysis to the less rigorous and less tedious methods of computational intelligence (CI). Power systems keep on increasing on the basis of geographical regions, assets additions, and introduction of new technologies in generation, transmission and distribution of electricity. Computation intelligent (CI) methods can give better solution in several conditions and are being widely applied in the electrical engineering applications. This paper highlights the application of computational intelligence methods in power system problems. Various types of CI methods, which are widely used in power system, are also discussed in the brief.*

Keywords- *Power systems, computational intelligence, artificial intelligence.*

I. INTRODUCTION

Computational intelligence (CI) is a new and modern tool for solving complex problems which are difficult to be solved by the conventional techniques. Heuristic optimization techniques are general purpose methods that are very flexible and can be applied to many types of objective functions and constraints. Recently, these new heuristic tools have been combined among themselves and new methods have emerged that combine elements of nature-based methods or which have their foundation in stochastic and simulation methods. Developing solutions with these tools offers two major advantages: development time is much shorter than when using more traditional approaches, and the systems are very robust, being relatively insensitive to noisy and/or missing data/information known as uncertainty.

Due to environmental, right-of-way and cost problems, there is an increased interest in better utilization of available power system capacities in both bundled and unbundled power systems. Patterns of generation that results in heavy flows, tend to incur greater losses, and to threaten stability and security, ultimately make certain generation patterns economically undesirable. Hence, new devices and resources such as flexible ac transmission systems (FACTS), distributed generations, smart grid technologies, etc. are being utilized. In the emerging area of power systems, computation intelligence plays a vital role in providing better solutions of the existing and new problems. This paper lists various potential areas of power systems and provides the roles of computational intelligence in the emerging power systems. A brief review of computational techniques is also presented.

1.1. NEED FOR CI IN POWER SYSTEMS

Power system analysis by conventional techniques becomes more difficult because of:

(i) Complex, versatile and large amount of information which is used in calculation, diagnosis and learning.
(ii) Increase in the computational time period and accuracy due to extensive and vast system data handling.

The modern power system operates close to the limits due to the ever increasing energy consumption and the extension of currently existing electrical transmission networks and lines. This situation requires a less conservative power system operation and control operation which is possible only by continuously checking the system states in a much more detail manner than it was necessary. Sophisticated computer tools are now the primary tools in solving the difficult problems that arise in the areas of power system planning, operation, diagnosis and design. Among these computer tools, Computational Intelligence has grown predominantly in recent years and has been applied to various areas of power systems.

II.VARIOUS COMPUTATIONAL INTELLIGENCE TECHNIQUES

Computational intelligence (CI) methods, which promise a global optimum or nearly so, such as expert system (ES), artificial neural network (ANN), genetic algorithm (GA), evolutionary computation (EC), fuzzy logic, etc. have been emerged in recent years in power systems applications as effective tools. These methods are also known as artificial intelligence (AI) in several works. In a practical power system, it is very important to have the human knowledge and experiences over a period of time due to various uncertainties, load variations, topology changes, etc. This section presents the overview of CI/AI methods (ANN, GA, fuzzy systems, EC, ES, ant colony search, Tabu search, etc.) used in power system applications.

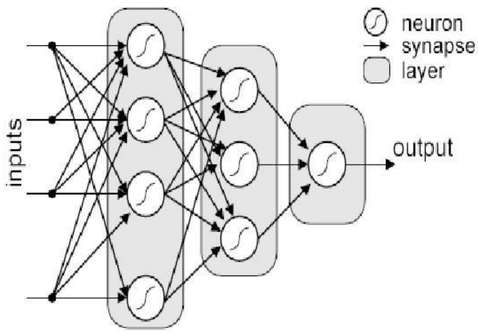
2.1. ARTIFICIAL NEURAL NETWORKS (ANN)

An artificial neural network (ANN) is an information-processing paradigm that is inspired by the biological nervous systems, such as the brain, process information (Bishop, 1995). Artificial Neural Networks are biologically inspired systems which convert a set of inputs into a set of outputs by a network of neurons, where each neuron produces one output as a function of inputs. A fundamental neuron can be considered as a processor which makes a simple non linear operation of its inputs producing a single output. The understanding of the working of neurons and the pattern of their interconnection can be used to construct computers for solving real world problems of classification of patterns and pattern recognition. They are classified by their architecture: number of layers and topology: connectivity pattern, feedforward or recurrent.

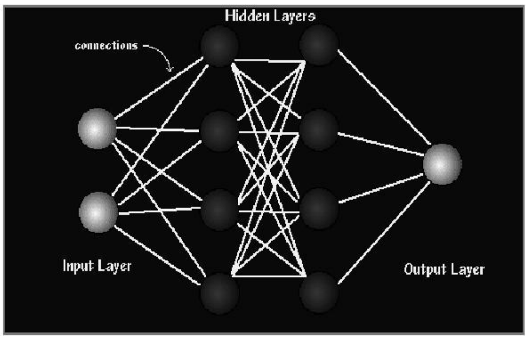
Input Layer: The nodes are input units which do not process the data and information but distribute this data and information to other units.

Hidden Layers: The nodes are hidden units that are not directly evident and visible. They provide the networks the ability to map or classify the nonlinear problems.

Output Layer: The nodes are output units, which encode possible values to be allocated to the case under consideration.



Architecture of a feedforward ANN



Typical structure of an ANN

2.1.1.Advantages:
(i) Speed of processing.
(ii) They do not need any appropriate knowledge of the system model.
(iii) They have the ability to handle situations of incomplete data and information, corrupt data.
(iv) They are fault tolerant.
(v) ANNs are fast and robust. They possess learning ability and adapt to the data.
(vi) They have the capability to generalize.

2.1.2. Disadvantages:
(i) Large dimensionality.
(ii) Results are always generated even if the input data are unreasonable.

(iii) They are not scalable i.e. once an ANN is trained to do certain task, it is difficult to extend for other tasks without retraining the neural network.

2.1.3.Applications:

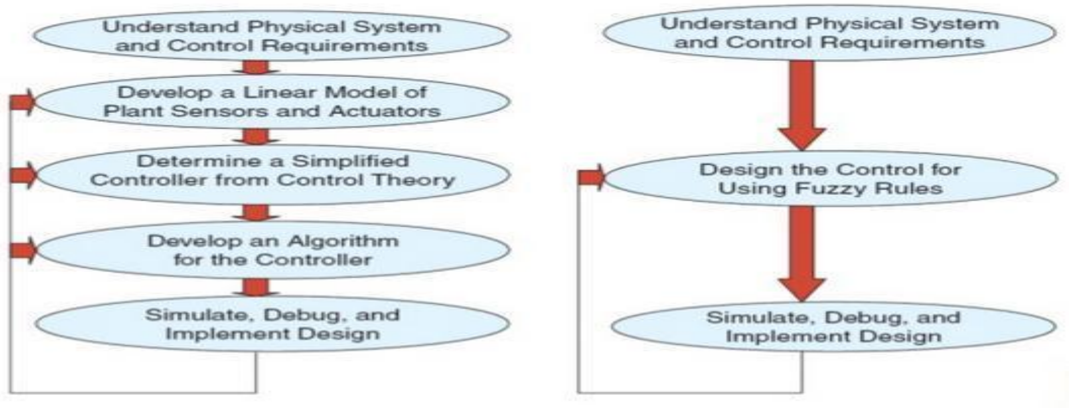
Power system problems concerning encoding of an unspecified non-linear function are appropriate for ANNs. ANNs can be particularly useful for problems which require quick results, like those in real time operation. This is because of their ability to quickly generate results after obtaining a set of inputs.

2.1.4. How ANNs can be used in power systems:

As ANNs operate on biological instincts and perform biological evaluation of real world problems, the problems in generation, transmission and distribution of electricity can be fed to the ANNs so that a suitable solution can be obtained. Given the constraints of a practical transmission and distribution system, the exact values of parameters can be determined. For example, the value of inductance, capacitance and resistance in a transmission line can be numerically calculated by ANNs taking in various factors like environmental factors, unbalancing conditions, and other possible problems. Also the values of resistance, capacitance and inductance of a transmission line can be given as inputs and a combined, normalized value of the parameters can be obtained. In this way skin effect and proximity effect can be reduced to a certain extent.

2.2. FUZZY LOGIC

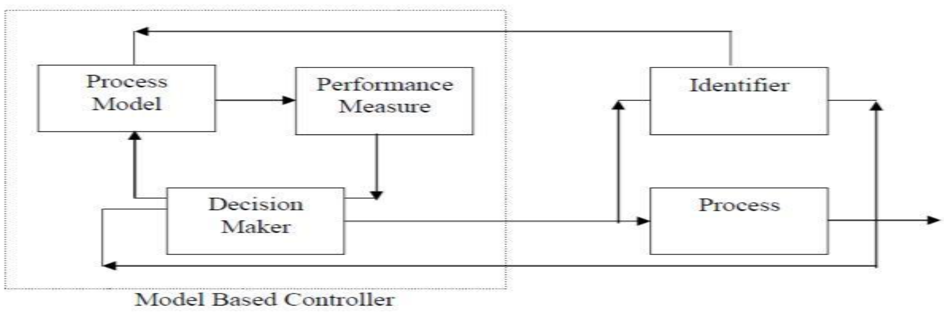
Fuzzy logic (FL) was developed by Zadeh (Zadeh, 1965) in 1964 to address uncertainty and imprecision, which widely exist in the engineering problems Fuzzy logic or Fuzzy systems are logical systems for standardization and formalization of approximate reasoning. It is similar to human decision making with an ability to produce exact and accurate solutions from certain or even approximate information and data. The reasoning in fuzzy logic is similar to human reasoning. Fuzzy logic is the way like which human brain works, and we can use this technology in machines so that they can perform somewhat like humans. Fuzzification provides superior expressive power, higher generality and an improved capability to model complex problems at low or moderate solution cost. Fuzzy logic allows a particular level of ambiguity throughout an analysis. Because this ambiguity can specify available information and minimize problem complexity, fuzzy logic is useful in many applications. For power systems, fuzzy logic is suitable for applications in many areas where the available information involves uncertainty. For example, a problem might involve logical reasoning, but can be applied to numerical, other than symbolic inputs and outputs. Fuzzy logic provide the conversions from numerical to symbolic inputs, and back again for the outputs.



Benefits of using fuzzy logic

2.2.1. Fuzzy Logic Controller

Simply put, it is a fuzzy code designed to control something, generally mechanical input. They can be in software or hardware mode and can be used in anything from small circuits to large mainframes. Adaptive fuzzy controllers learn to control complex process much similar to as we do.



2.2.2. Applications:

(i) Stability analysis and enhancement
(ii) Power system control

(iii) Fault diagnosis

(iv) Security assessment

(v) Load forecasting

(vi) Reactive power planning and its control

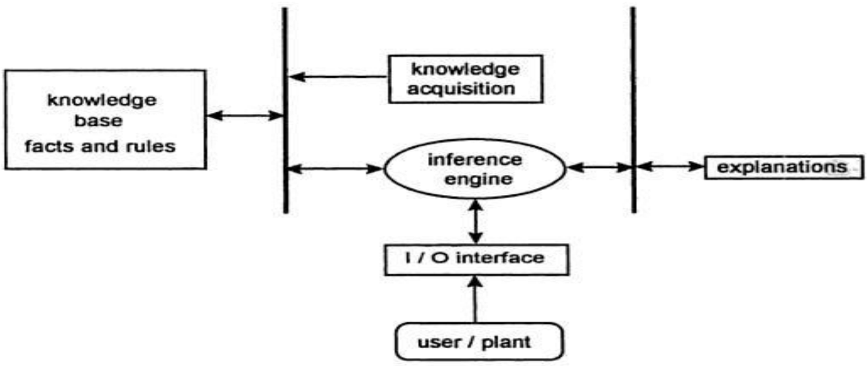
(vii) State estimation

2.2.3. How fuzzy logic can be used in power systems:

Fuzzy logic can be used for designing the physical components of power systems. They can be used in anything from small circuits to large mainframes. They can be used to increase the efficiency of the components used in power systems. As most of the data used in power system analysis are approximate values and assumptions, fuzzy logic can be of great use to derive a stable, exact and ambiguity-free output.

2.3.EXPERT SYSTEMS

An expert system obtains the knowledge of a human expert in a narrow specified domain into a machine implementable form. Expert systems are computer programs which have proficiency and competence in a particular field. This knowledge is generally stored separately from the program's procedural part and may be stored in one of the many forms, like rules, decision trees, models, and frames. They are also called as knowledge based systems or rule based systems. Expert systems use the interface mechanism and knowledge to solve problems which cannot be or difficult to be solved by human skill and intellect.



Structure of an Expert System

2.3.1. Advantages:
(i) It is permanent and consistent.
(ii) It can be easily documented.

(iii) It can be easily transferred or reproduced.

2.3.2. Disadvantage:
Expert Systems are unable to learn or adapt to new problems or situations.

2.3.3. Applications:

Many areas of applications in power systems match the abilities of expert systems like decision making, archiving knowledge, and solving problems by reasoning, heuristics and judgment. Expert systems are especially useful for these problems when a large amount of data and information must be processed in a short period of time.

2.3.4. How expert systems can be used in power systems:

Since expert systems are basically computer programs, the process of writing codes for these programs is simpler than actually calculating and estimating the value of parameters used in generation, transmission and distribution. Any modifications even after design can be easily done because they are computer programs. Virtually, estimation of these values can be done and further research for increasing the efficiency of the process can be also performed.

2.4. GENETIC ALGORITHMS (GA)

Genetic algorithm is an optimization technique based on the study of natural selection and natural genetics. Its basic principle is that the fittest individual of a population has the highest probability and possibility for survival. Genetic algorithm gives a global technique based on biological metaphors. The Genetic algorithm can be differentiated from other optimization methods by:

(i) Genetic algorithm works on the coding of the variables set instead of the actual variables.

(ii) Genetic algorithm looks for optimal points through a population of possible solution points, and not a single point.

(iii) Genetic algorithm uses only objective function information.

(iv) Genetic algorithm uses probability transition laws, not the deterministic laws.

Genetic algorithm is derived from an elementary model of population genetics. It has following components:

(i) Chromosomal representation of the variable describing an individual.

(ii) An initial population of individuals.

(iii) An evaluation function which plays the environment's part, ranking the individuals in terms of their fitness which is their ability to survive.

(iv) Genetic operators which determine the configuration of a new population generated from the previous one by a procedure.

(v) Values for the parameters that the GA uses.

2.4.1.Applications:

Areas of applications in power systems include:

(i) Planning – Wind turbine positioning, reactive power optimisation, network feeder routing, and capacitor placement.

(ii) Operation – Hydro-thermal plant coordination, maintenance scheduling, loss minimisation, load management, control of FACTS.

(iii) Analysis – Harmonic distortion reduction, filter design, load frequency control, load flow.

2.4.2. How genetic algorithms can be used in power systems:

As genetic algorithms are based on the principle of survival of fittest, several methods for increasing the efficiency of power system processes and increasing power output can be proposed. Out of these methods, using genetic algorithms, the best method which withstands all constraints can be selected as it is the best method among the proposed methods (survival of fittest).

2.5. EVOLUTIONARY COMPUTATION: EVOLUTIONARY STRATEGIES AND EVOLUTIONARY PROGRAMMING

Natural evolution is a hypothetical population -based optimization process. Simulating this process on a computer results in stochastic optimization techniques that can often perform better than classical methods of optimization for real-world problems. Evolutionary computation (EC) is based on the Darwin's principle of 'survival of the fittest strategy'. An evolutionary algorithm begins by initializing a population of solutions to a problem. New solutions are then created by randomly varying those of the initial population. All solutions are measured with respect to how well they address the task. Finally, a selection criterion is applied to weed out those solutions, which are below standard. The process is iterated using the selected set of solutions until a specific criterion is met. The advantages of EC are adaptability to change and ability to generate good enough solutions but it needs to be understood in relation to computing requirements and convergence properties. EC can be subdivided into GA, evolution strategies, evolutionary programming (EP), genetic programming, classified systems, simulated annealing (SA), etc. The first work in the field of evolutionary computation was reported by Fraser in 1957 (Fraser, 1957) to study the aspects of genetic system using a computer. After some time, a number of evolutionary inspired optimization techniques were developed.

Evolution strategies (ES) employ real-coded variables and, in its original form, it relied on mutation as the search operator and a population size of one. Since then, it has evolved to share many features with GA. The major similarity between these two types of algorithms is that they both maintain populations of potential solutions and use a selection mechanism for choosing the best individuals from the population. The main differences are:

- ESs operates directly on floating point vectors while classical GAs operate on binary strings,
- GAs rely mainly on recombination to explore the search space while ES uses mutation as the dominant operator and
- ES is an abstraction of evolution at individual behavior level, stressing the behavioral link between an individual and its offspring, while GA maintains the genetic link.

Evolutionary programming (EP), which is a stochastic optimization strategy similar to GA, places emphasis on the behavioral linkage between parents and their offspring, rather than seeking to emulate specific genetic operators as observed in nature. EP is similar to evolutionary strategies, although the two approaches were developed independently. Like ES and GA, EP is a useful method of optimization when other techniques such as gradient descent or direct analytical discovery are not possible. Combinatorial and real-valued function optimizations, in which the optimization surface or fitness landscape is "rugged" and possessing many locally optimal solutions, are well suited for evolutionary programming

2.6. SIMULATED ANNEALING

This method was independently described by Scott Kirkpatrick, C. Daniel Gelatt and Mario P. Vecchi in 1983 (Kirkpatrick *et al.*, 1983), and by Vlado CČerny in 1985 (Cerny, 1985). Based on the annealing process in the statistical mechanics, the simulated annealing (SA) was introduced for solving complicated combinatorial optimization problems. In a large combinatorial optimization problem, an appropriate perturbation mechanism, cost function, solution space, and cooling schedule are required in order to find an optimal solution with simulated annealing. SA is effective in network reconfiguration problems for large-scale distribution systems and its search capability becomes more significant as the system size increases. Moreover, the cost function with a smoothing strategy enables the SA to escape more easily from local minima and to reach rapidly to the vicinity of an optimal solution.

The advantages of SA are its general applicability to deal with arbitrary systems and cost functions; its ability to refine optimal solution; and its simplicity of implementation even for complex problems. The major drawback of SA is repeated annealing. This method cannot tell whether it has found optimal solution or not. Some other methods (e.g. branch and bound) are required to do this. SA has been used in various power system applications like transmission expansion planning, unit commitment, maintenance scheduling, etc.

2.7. ANT COLONY AND TABU SEARCH

Dorigo introduced the ant colony search (ACS) system, first time, in 1992 (Dorigo, 1992). ACS techniques take inspiration from the behavior of real ant colonies and are used to solve functional or combinational problems. ACS algorithms to some extent mimic the behavior of real ants. The main characteristics of ACS are positive feedback for recovery of good solutions, distributed computation, which avoids premature convergence, and the use of a constructive heuristic to find acceptable solutions in the early stages of the search process. The main drawback of the ACS technique is poor computational features. ACS technique has been mainly used in finding the shortest route for transmission network.

Tabu search (TS) is basically a gradient-descent search with memory. The memory preserves a number of previously visited states along with a number of states that might be considered unwanted. This information is stored in a Tabu list. The definition of a state, the area around it and the length of the Tabu list are critical design parameters. In addition to these Tabu parameters, two extra parameters are often used such as aspiration and diversification. Aspiration is used when all the neighboring states of the current state are also included in the Tabu list. In that case, the Tabu obstacle is overridden by selecting a new state. Diversification adds randomness to this otherwise deterministic search. If the Tabu search is not converging, the search is reset randomly.
TS is an iterative improvement procedure that starts from some initial solution and attempts to determine a better solution in the manner of a 'greatest descent neighborhood' search algorithm. Basic components of TS are the moves, Tabu list and aspiration level. TS is a metahuristic search to solve global optimization problem, based on multi-level memory management and response exploration. TS has been used in various power system application like transmission planning, optimal capacitor placement, unit commitment, hydrothermal scheduling , fault diagnosis/alarm processing, reactive power planning, etc.

2.8. PARTICLE SWARM OPTIMIZATION

The particle swarm optimization (PSO) method introduced by Kennedy and Eberhart (Kennedy *et al*., 1995) is a self-educating optimisation algorithm that can be applied to any nonlinear optimisation problem. In PSO, the potential solutions, called particles,fly through the problem space by following the best fitness of the particles. It is easily implemented in most programming languages and has proven to be both very fast and effective when applied to a diverse set of optimization problems. In PSO, the particles are "flown" through the problem space by following the current optimum particles. Each particle keeps the track of its coordinate in the problem space, which is associated with the best solution (fitness) that it has achieved so far. This implies that each particle has memory, which allows it to remember the best position on the feasible search space that has ever visited. This value is commonly called as *pbest* . Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighborhood of the particle. This location is commonly called as *gbest.*

The position and velocity vectors of the i[th] particle of a d-dimensional search space can be represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$ and $V_i = (v_{i1}, v_{i2}, \ldots, v_{id})$ respectively. On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as $pbest_i = (P_{i1}, P_{i2}, \ldots, P_{id})$. If the g^{th} particle is the best among all particles in the group so far, it is represented as $gbest = pbest_g (P_{g1}, P_{g2}, \ldots P_{gd})$. The particle tries to modify its position using the current velocity and the distance from *pbest* and *gbest* . The modified velocity and position of each particle for fitness evaluation in the next iteration are calculated using the following equations

$$v_{id}^{k+1} = w \times v_{id}^{k} + c_1 \times rand_1 \times (pbest_{id} - x_{id}^{k}) + c_2 \times rand_2 \times (gbest_{gd} - x_{id}^{k}) \quad (1)$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \quad (2)$$

where, w is the inertia weight parameter, which controls the global and local exploration capabilities of the particle. c_1, c_2 are cognitive and social coefficients and $rand_1$ and $rand_2$ are random numbers between 0 and 1. A large inertia weight factor is used during initial exploration and its value is gradually reduced as the search proceeds. The concept of time-varying inertial weight (TVIM) is given by

$$w = (w_{max} - w_{min}) \times \frac{iter_{max} - iter}{iter_{max}} + w_{Min} \quad (3)$$

where $iter_{max}$ is the maximum number of iterations.

The velocity update expression (1) can be explained as follows. Without the second and third terms, the first term (representing inertia) will keep a particle flying in the same direction until it hits the boundary. Therefore, the first term tries to explore new areas and corresponds to the diversification in the search procedure. In contrast, without the first term, the velocity of the flying particle is only determined by using its current position and its best positions in history. Therefore, the second representing memory) and third terms (representing cooperation) try to converge the particles to their *Pbest* and/or *Gbest* and correspond to the intensification in the search procedure.

2.9. SUPPORT VECTOR MACHINES

Support vector machine (SVM) is one of the relatively new and promising methods for learning, separating functions in pattern recognition (classification) tasks as well as performing function estimation in regression problems. It is originated from supervised learning systems derived from the statistical learning theory introduced by Vapnik for "distribution free learning from data" (Vapnik, 1998). In this method, the data are mapped into a high dimensional space via a nonlinear map, and using this high dimensional space, an optimal separating hyper-plane or linear regression function is constructed. This process involves a quadratic programming problem and produces a global optimal solution. The great advantage of SVM approach is that it greatly reduces the number of operations in the learning mode and minimizes the generalization error on the test set under the structural risk minimization (SRM) principle. Main objective of the SRM principle is to choose the model complexity optimally for a given training sample. The input space in a SVM is nonlinearly mapped onto a high dimensional feature space. The idea is to map the feature space into a much bigger space so that the boundary is linear in the new space. SVMs are able to find non-linear boundaries if classes are linearly non-separable. Another important feature of the SVM is the use of kernels. Kernel representations offer an alternative solution by nonlinearly projecting the input space onto a high dimensional feature space. The advantage of using SVMs for classification is the generalization performance. SVM performs better than neural networks in term of generalization. There is problem of over fitting or under fitting if so many training data or too few training data are used. The computational complexity is other factor for the choice of SVMs as classifier. The other advantage of SVM based system is that it is straight forward to extend the system when new types of cases are added to the classifier.

III.CURRENT APPLICATION OF CI IN POWER SYSTEMS

Several problems in power systems cannot be solved by conventional techniques are based on several requirements which may not feasible all the time. In these situations, artificial intelligence techniques are the obvious and the only option. Areas of application of AI in power systems are:

(i) Operation of power system like unit commitment, hydro-thermal coordination, economic dispatch, congestion management, maintenance scheduling, state estimation, load and power flow.

(ii) Planning of power system like generation expansion planning, power system reliability, transmission expansion planning, reactive power planning.

(iii) Control of power system like voltage control, stability control, power flow control, load frequency control.

(iv) Control of power plants like fuel cell power plant control, thermal power plant control.

(v) Control of network like location, sizing and control of FACTS devices.

(vi) Electricity markets like strategies for bidding, analysis of electricity markets.

(vii) Automation of power system like restoration, management, fault diagnosis, network security.

(viii) Applications of distribution system like planning and operation of distribution system, demand side response and demand side management, operation and control of smart grids, network reconfiguration.

(ix) Applications of distributed generation like distributed generation planning, solar photovoltaic power plant control, wind turbine plant control and renewable energy resources.

(x) Forecasting application like short term and long term load forecasting, electricity market forecasting, solar power forecasting, wind power forecasting.

IV. CONCLUSION

The main feature of power system design and planning is reliability, which was conventionally evaluated using deterministic methods. Moreover, conventional techniques don't fulfill the probabilistic essence of power systems. This leads to increase in operating and maintenance costs. Plenty of research is performed to utilize the current interest CI for power system applications. A lot of research is yet to be performed to perceive full advantages of this upcoming technology for improving the efficiency of electricity market investment, distributed control and monitoring, efficient system analysis, particularly power systems which use renewable energy resources for operation.

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