Computational Intelligence in Electrical Power Systems: A Survey of Emerging Approaches

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Abstract
Development of solutions to optimisation problems (including electrical power systems) has remained an active research area in the recent decades, with interests in the field growing rapidly because of the high importance of electricity, even as the world's energy demand is on a daily increase. Problems in this sector are characterised by increased complexity and dynamism; and artificial intelligent tools have proved the only means of realising optimal and robust solutions. This paper contributes an up-to-date survey of the successful artificially intelligent approaches used to solve electrical power system problems, including their respective application areas. It groups the approaches against the corresponding problems they solve; and makes a critical and comparative analysis of the approaches in terms of their merits and demerits. This is of great importance to researchers and experimentalists in this field. These emerging techniques have provided good platforms for development of their various hybrids and variants.

Keywords*:* Artificial intelligence, Electrical power systems, Machine learning, Memetic algorithms, Nature-inspired algorithms.

1. INTRODUCTION

Problems facing development of solution algorithms to electrical power system problems include: increasing the size of the power system, on-line applications of automatic control, and the need to achieve optimal output. Several contributions have been made to tackle these problems, but it is worthy of note however, that amongst the existing approaches, no single method meets all the desirable requirements of an ideal solution. In any particular situation, the choice of any method is a good compromise between various capabilities of the existing methods [1]. Problems faced in the electrical power system sector have the following characteristics: (1) They are formulated on systems operating at steady state conditions, with equations consisting of a set of non-linear equations to be solved simultaneously; (2) Solutions to these equations are not unique; (3) The numbers of unknown variables in the equations are usually more than the number of equations. A good solution approach must have properties from a combination of some of the following features: high speed, low storage requirements, reliability, and versatility in handling various adjustments, simplicity and high-degree of accuracy [2]. Solution approaches to electrical power system problems fall under three categories:

1. Mathematical programming methods;

2. Computational intelligent methods;
3. Hybrid methods.

The traditional/mathematical programming methods include: bus admittance matrix method, Gauss-Seidel iterative, Newton-Raphson, linear programming, non-linear programming, dynamic programming, interior point, Lambda iteration, fast-decoupled algorithms, integer programming, quadratic programming, decomposition techniques [1, 2, 3, 4], etc. In most of these algorithms, optimality of solutions was mathematically formulated, and could be applied to large-scale problems. They have no problem-specific parameters, and most of them have high computational efficiency, with ease of implementation. However, solutions obtained using the techniques have their inherent limitations, and solutions for large-scale systems are not very simple. Many of them fail to get optimal solutions, with a possibility of getting stuck in local optima. Despite the successes of mathematical programming methods, the above identified problems have pushed development of solutions to electrical power systems in the recent decades from the traditional iterative methods to stochastic search methods. Most power problems require the use of facilities to store human knowledge, operators' judgment/experience, and variations in load and network uncertainties [4].

Artificial intelligence is the intelligence exhibited by machines or software systems. A leading and successful approach to artificial intelligence is the computational intelligence [5]. As a scientific as well as engineering discipline, the purpose (science) of computational intelligence is the understanding of underlying principles behind intelligent agents; while the methodology (engineering) involves the design, implementation and experimentation with systems which perform tasks that are considered intelligent. Such tasks include: knowledge, reasoning, learning, planning, communication, perception, manipulation, etc.

2. COMPUTATIONAL INTELLIGENCE METHODOLOGIES

Computational intelligence methodologies are of three broad categories: *machine learning algorithms, nature-inspired algorithms* and *hybrid methods.* Table 1 summarizes this classification.

2.1 Machine Learning Algorithms

Machine learning deals with the study and design of systems that have the capability of learning from data. The systems work by prediction, based on previously known properties learned from the data. The most common and widely used machine learning algorithms in solving electrical power system problems are: Artificial Neural Networks, Fuzzy Logic, Expert Systems, Bayesian Networks, and Support Vector Machines.

2.1.1 Artificial Neural Network

Artificial Neural Network (ANN), inspired by the work of Warren McCulloch and Walter Pitts: "a logical calculus of the ideas imminent in nervous activity" [6], models the construction and behavior of the human brain using man made technology. An ANN is a layered network of artificial neurons, working in analogy to biological neurons. The architecture of a typical ANN (consisting of three types of layers/neurons) is shown in figure 1. The advantages of ANNs that facilitate its usage are: speed, robustness, ability to learn, ability to adapt to training data, and appropriateness for non-linear modeling. However, for complex problems ANNs need to have many inputs and/or several layers of inputs; with consequently many parameters, much time is required for training, and good results are far from guaranteed. Recent applications of ANN to electrical power system optimisation are in the areas of: load forecasting, voltage security, monitoring and control, unit commitment (UC), economic load dispatch (ELD), fault diagnosis, security assessment and power system stability [7-9].

Table 1. Classification of computational intelligence methodologies/approaches

Machine Learning Approaches	Artificial Neural Network Fuzzy Logic Expert System Bayesian Network Support Vector Machine		
Nature-Inspired Approaches	Bio-Inspired Algorithms	Evolutionary Algorithm	Genetic Algorithm Genetic Programming Evolutionary Programming Evolutionary Strategy Differential Evolution Estimation of Distribution Algorithm
		Swarm Intelligence	Ant Colony Optimisation Particle Swarm Optimisation Bee Colony Optimisation
	Physics-Based Algorithms	Harmony Search	
	Chemistry-Based Algorithms	Simulated Annealing	
	Memetic Algorithms	Artificial Immune System Shuffled Frog Leaping Algorithm Group Search Optimizer Biogeography-Based Optimisation	
Hybrid Methods	Combination of two or more of the other approaches		

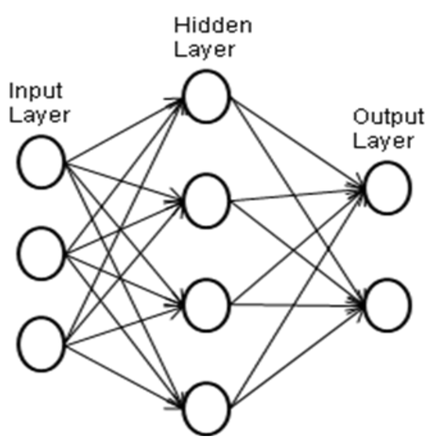

Figure 1. A multi-layered artificial neural network

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2.1.2 Fuzzy Logic

Fuzzy Logic (FL), developed in 1964 by Lotfi A. Zadeh [10], is a superset of Boolean logic, and handles the concept of partial truth. It provides rules and functions that permitted natural language queries, a means of calculating intermediate values between absolute TRUE and absolute FALSE, with resulting values between 0 and 1. FL aims to address uncertainty and imprecision which widely exist in the engineering problems and was first used in 1979 for solving power system problems, with application to voltage and reactive power control, load forecasting, fault diagnosis, power system protection/relaying, stability, and power system control [4, 11]. Its application to active power generation is very limited, unless as a hybrid tool with other approaches [12].

2.1.3 Expert System

Expert System, first proposed in 1971 by Feigenbaum *et al* [13], is a knowledge-based method which uses the knowledge gained from application domain experts, available via a suitable rule-based interface, to solve problems that are difficult enough to require human expertise for their solution [4, 14]. The systems are permanent and consistent in their results. They can be easily be transferred, reproduced and documented. In the recent decades, expert system has been applied in the areas of power system planning, alarm processing, fault diagnosis, power system protection, reactive power/voltage control, as well as load, bid and price forecasting [4, 15, 16]. However, expert system suffers from knowledge bottleneck problem [14], as it does not learn or adapt to new situations.

2.1.4 Bayesian Network

A Bayesian network is a probabilistic graphical model whose nodes represent a set of random variables, connected by edges which represent conditional dependencies or relationships through a directed acyclic graph [17]. Each node has a conditional probability table, which are learnt from a given network structure with independence assumptions, as shown in figure 2. The number of parameters in the network is proportional to the directed edges in the network due to the independent assumptions. The Bayesian learning is a complex process that requires a thorough knowledge of the problem domain; it is intuitive in nature. Bayesian networks are widely used in power system components fault diagnosis and detection [17, 18].

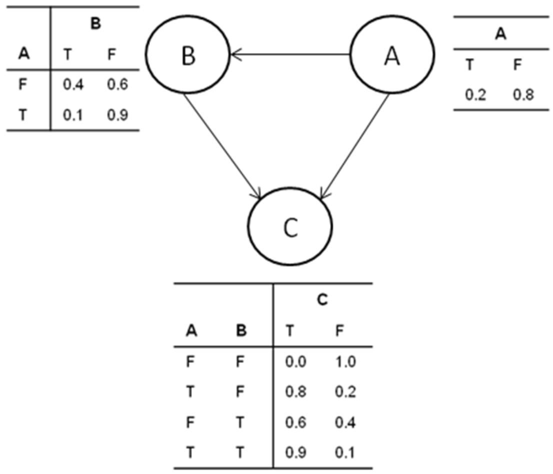

Figure 2. A typical Bayesian network

2.1.5 Support Vector Machine

Support Vector Machine (SVM) originated from both supervised and statistical learning theories of Vapnik in 1998 [19]. It is relatively and comparatively a new machine learning technique which is based on structural risk minimisation (SRM), where there is a mapping of data from given dimensional space into higher ones, and from these higher dimensional spaces, optimal separating hyper-planes are constructed to solve quadratic programming problems [14]. Under the SRM principle, the SVM approach reduces the number of learning operations and minimises computational errors on the test data set. SVM is a regression prediction/text classification tool that uses machine learning theory to maximise prediction accuracy while at the same time avoiding data that does fall in the particular classifying zone. SVMs are generally used in electrical power systems load forecasting and prediction [20, 21].

2.2 Nature-Inspired Algorithms

These are algorithms developed for solving optimisation problems by drawing inspiration from nature [22]. These algorithms are classified as: Biological-inspired (Bio-inspired), Physics-based and Chemistry-based algorithms [23, 24]. Bio-inspired algorithms are population-based algorithms which imitate biological processes (evolution and natural hereditary). Two classes of these algorithms are: Evolutionary Algorithm (EA) and Swarm Intelligence (SI). Physics and Chemistry-based algorithms are developed by drawing inspiration from some physical or chemical laws. Common examples are Simulated Annealing (SA) and Harmony Search (HS). Recently, nature-inspired Memetic Algorithms (MA) [25], have been developed for solving power systems problems, most of which combine the evolutionary nature of EAs with the swarm behaviour of SIs. Examples include: Artificial Immune Systems, Shuffled Frog Leaping Algorithm, Group Search Optimizer and Biogeography-Based Optimisation.

2.2.1 Evolutionary Algorithm

This is a non-deterministic, nature-inspired, population-based optimisation approach which mimics the process of biological evolution, and bear direct analogy to Charles Darwin's theory of natural selection and evolution [26, 27]. There are several varieties of Evolutionary Algorithm (EA) based on alternative solution structures, search operators and implementation aspects. Common examples are: Genetic Algorithm, Evolutionary Programming, Genetic Programming, Evolution Strategies, Differential Evolution, and Estimation of Distribution Algorithms. A general work flow of EAs is shown in figure 3.

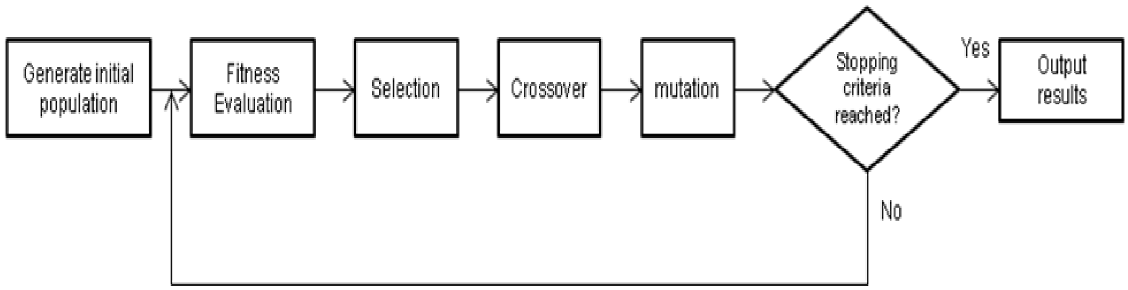

Figure 3. A general work flow of evolutionary algorithms

*A. **Genetic Algorithm***

Initially developed in the 1960s by John Holland [26], Genetic Algorithm (GA) is inspired by nature's principle of 'survival-of-the-fittest' and evolutionist theory, based on the concept of competitive natural selection and origin of species [27]. Naturally, stronger species reproduce more, and pass on their genetic structure to their future generations, while the weaker ones face the problem of extinction. GA is the basis for all other evolutionary algorithms, and is an actively growing research area in both EA and the entire field of computational intelligence in solving a range of electrical power system problems, including: transmission expansion planning, power control, UC, ELD, hydrothermal scheduling, security assessment and optimisation of power flow controllers [4, 28-32].

*B. **Evolutionary Programming***

First conceived by Lawrence Fogel [33], Evolutionary Programming (EP) is a mutation-based EA (genetic linkage between parents and their offspring). The structure of the chromosome is fixed as in GA, while the parameters are allowed to gradually evolve. The approach was extended to real-parameter optimisation problems by David Fogel [34]. EP relies mostly on mutation and selection (without crossover). EP has extensively been applied in solving a wide range of power system problems, including: UC, ELD, voltage and reactive power control, generation, transmission and distribution expansion planning, hydrothermal scheduling and deregulated system [35, 36]. The major disadvantage of EP is its slow convergence.

*C. **Genetic Programming***

Genetic Programming (GP), named by John Koza [37], is a specialization of GA, but the individual chromosomes are computer programs that perform user-defined tasks. While GA works on fixed-length chromosomes, GP manipulates variable length structures. Originally, GP was mainly used in solving relatively simple problems due to its computational intensive nature; and in EA to evolve computer programs, represented in the memory as a function tree. But with improvements in the technology, its usage was extended to quantum computing, sorting, searching, games theory and electronic design, but with minimal applications to electrical power system problems, especially in areas of general power system planning and operation [38, 39]. Sean Luke *et al* [40], developed and ECJ (Evolutionary Computation in Java), an EA/GP project toolkit which consists of several packages - classes, methods and objects that are designed to carry out several activities, specified in parameters files.

D. Evolution Strategy

Initially proposed in the 1960s and further developed in the 1970 by Bienert, Rechenberg and Schwefel [41], Evolution Strategy (ES) also relies on mutation and selection as its search operators, with a population size of "one" [14]. Although ES shares a lot of similarities with GA, however, ES operates only on floating point vectors, uses mutation as a primary operator, and emphasizes more on behavioral (than genetic) link between parents and offspring. Applications of ES to electrical power systems are in design of flexible alternating current transmission systems (FACTS) devices and reactive power control [14, 42].

E. Differential Evolution

Differential Evolution (DE) was first proposed in 1995 by Storn and Price as an improved version of GA [43]. It uses few control parameters (which require minimum tuning, and remain fixed all through the process of optimisation. As in GA, DE makes use of three basic genetic operators: mutation, crossover and selection; but like ES, it relies mainly on mutation to achieve its solutions. The advantages of DE include: ease of use, simple structure and implementation, fastness, and local searching property [43-46]. But there is a disadvantageous tendency of being trapped in a local optimum or attaining premature convergence [43, 45]. DE has a wide range of application to solving power system optimisation problems, including: UC, ELD, voltage stability/security, real power stability and control, generation, transmission and distribution expansion planning and deregulated electricity systems [44 – 50].

F. Estimation of Distribution Algorithm

Estimation of Distribution Algorithm (EDA), also known as Probabilistic Model Building Genetic Algorithm [51], is motivated by the idea of discovering and exploiting interactions between variables in the solution. It estimates a probability distribution from population of solutions, and samples it to generate the next population. Through this, it builds probabilistic models to prevent disruption of solutions, as they move on from one generation to another.

EDA does not only solve difficult problems, but also provides information on how the problem was previously solved [52]. This is a feature that makes the algorithm stand out from other optimisation techniques. At moment, limited electrical power system applications of EDA are in the areas of UC, ELD, hydrothermal scheduling and controller design [53, 54, 55].

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2.2.2 Swarm Intelligence

Swarm Intelligence (SI) is a computational intelligent algorithm that is inspired by natural swarm behavior (of insects, birds and fishes) in developing solutions to problems [56]. SI originated from the study of colonies, or swarms of social organisms and consists of three main algorithms: Ant Colony Optimisation, Particle Swarm Optimisation, and Bee Colony Optimisation.

A. Ant Colony Optimisation

Developed in 1992 by Dorigo [57], Ant Colony Optimisation (ACO) deals with artificial systems, taking inspiration from the behaviour of real biological ants, in their quest to seek optimal paths between their colonies and sources of food; and used in solving discrete optimisation problems. The idea is that when one ant finds a reasonably good 'path', other ants are more likely to follow that path. This is what makes ants to follow a single path. ACO has a characteristic positive feedback for recovery of good solutions and distributed computation which helps in avoiding premature convergence, but its main drawback is poor computational complexity [14]. ACO has a wide range of learning applications, including: ordering, scheduling, vehicle routing, classification, and assignment problems. The recent applications of ACO to solving power system problems are in the areas of UC, ELD, determining the shortest route for power transmission and distribution networks [14, 58, 59].

B. Particle Swarm Optimisation

Introduced in 1995 by Kennedy and Eberhart [60], Particle Swarm Optimisation (PSO) is a population-based, global optimisation approach, modeled on the social behaviour of organisms, such as flocking of birds and schooling of fishes. Potential solutions in the search space are called 'particles'. Each particle keeps track of its position coordinates, and moves towards the best known position. Thus, the movement of the particles is determined by both their best locally know positions, *pbest*; as well as overall best positions, *gbest*, which are periodically updated as the particles discover new better positions [14]. Particles also have memories, which enable them to remember the best position they had visited. The population of the particles is called a swarm. Since its introduction, there exist several modifications and variants of PSO, including: binary PSO, real-valued PSO, integer PSO, vector PSO, Gaussian PSO, adaptive PSO, discrete PSO [61]. PSO is the most widely used of the three SI approaches in solving ELD problems in recent decades, and although it has the ability of quick convergence through exploration, but it is very slow in exploitation. It encounters a problem while escaping from local optima when stuck. Recent applications of PSO to electrical power systems are in the areas of UC, ELD, power and voltage control, power system reliability and security, power generation, transmission and distribution network, load forecasting and deregulated systems [62, 63, 64].

C. Bee Colony Optimisation

Proposed in 2005 by Karaboga [65], Bee Colony Optimisation (BCO) is an optimisation approach motivated by intelligent food foraging behaviour of swarm of honey bees. Three groups of bees make up a colony: employed bees, onlookers and scouts. For each food source, only one employed bee is assumed. Several mechanisms (such as waggle dance) are employed to find optimal location of food sources and search new ones [66]. An onlooker watches the dances of employed bees and chooses food sources depending on dances, while a scout is an employed bee whose food source has been abandoned, and hence starts to find a new food source. The position of a food source is a candidate solution; the ‘amount’ or quality of the food source represents the fitness, while the number of the employed bees is equal to the number of solutions in the population. An employed bee also has a memory feature to track the position of new food source. Applications of BCO to real-world power system problems are in the areas of UC, ELD and deregulated systems [66, 67, 68].

2.2.3 Artificial Immune System

Artificial Immune System (AIS), inspired by the works of Farmer, Packard and Perelson in 1986 [69], is a class of computationally intelligent systems based on the principles and processes of the immune system. The algorithm combines the characteristics of learning and memory of the system to solve a problem, which investigates the application of the immune systems to solving computational problems from mathematics, science and engineering. It adopts learning, memory and associative retrieval system to solve recognition, classification and optimisation tasks. Four common algorithms used in AIS are: clonal selection algorithm, negative selection algorithm, immune network algorithm and dendritic cell algorithm. Common application areas of AIS include: functions approximation, pattern recognition, anomaly detection, network security, noise tolerance. In power system operations, AIS has been applied to voltage stability, UC, real and reactive power dispatch, transmission and distribution networks design and deregulated power systems [70, 71, 72, 73].

2.2.4 Shuffled Frog Leaping Algorithm

Proposed by Eusuff and Lansey in 2003 [74], the Shuffled Frog Leaping Algorithm (SFLA) is a recent nature-inspired MA, which is derived from a population of frogs that co-operate with each other (when searching for food), to achieve a unified behavior for the whole system [75], with each frog representing a feasible solution, and the frogs are distributed into different sets of the population called memeplexes. SFLA combines the benefits of evolution-based EAs and social behavior-based PSO.

Frogs in SFLA are similar to chromosomes in EAs. The operators involved in the algorithm are the number of frogs, number of memeplexes, number of generation for each memeplex before shuffling, number of shuffling iterations, and maximum step size. During a shuffling process, vital information is passed among memeplexes. Shuffling also helps in improving the quality of frogs’ ideas after interaction with frogs from other memeplexes.

With its simplicity, robustness and fastness, SFLA proves to be very efficient in calculating the global optima of many problems with large search space, and has been used to find high quality solutions to large-scale and complex power problems, including: voltage stability and security, UC, static and dynamic ELD, fault diagnosis and protection, generation, transmission and distribution expansion planning, FACTS devices design, and deregulated power systems [74, 75, 76]. A workflow diagram of SFLA is illustrated in figure 4.

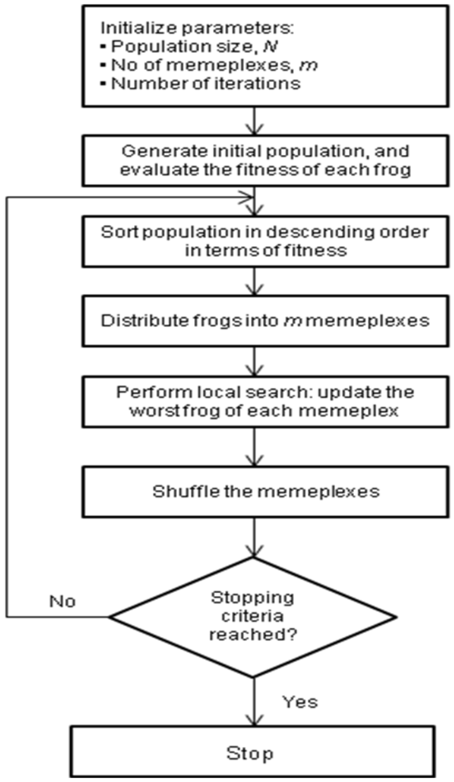

Figure 4. A workflow illustration of shuffled frog leaping algorithm

2.2.5 Group Search Optimizer

The Group Search Optimizer (GSO) is a search algorithm that draws inspiration from group-living, typically found in the animal community [77]. It employs the concept of resources searching mechanism (a movement behavior whereby animals search for food, mate or nesting sites), using producer-scrounger (PS) model to design optimal searching strategies. Although individual animals can try to search sparse resources which are randomly located alone, but group search aids them in information sharing which helps in increasing search rates and reduce success variance.

A group is made up of producers, scroungers and rangers. The behaviour of the first two is based on the PS model. Producing simply mean searching for food, while scrounging is to join the group for foraging. Ranging is performing random walk in the search space [78]. The PS model is simplified for accuracy and ease of computation by assuming only one producer with several scroungers and rangers at each search point [77]. The workflow diagram of a GSO is illustrated in figure 5. Other application areas are: distributed generation; transmission and distribution network expansion planning; and deregulated systems [77, 79, 80].

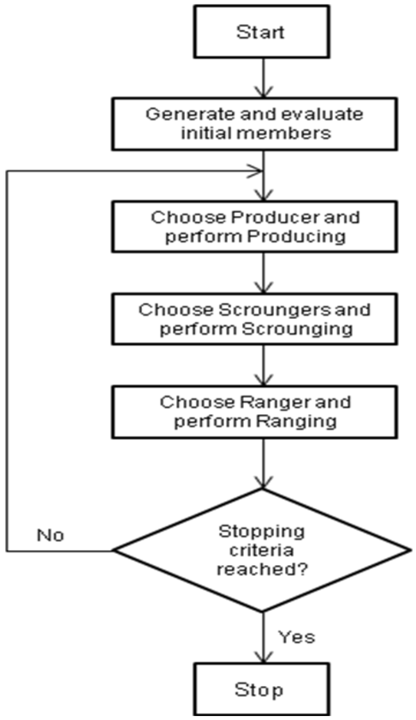

Figure 5. A workflow illustration of group search optimizer

2.2.6 Biogeography-Based Optimisation

First developed in 2008 by Simon [81], drawing inspiration from natural process and geography, Biogeography-Based Optimisation (BBO) is a global optimisation algorithm that studies the distribution of species of organisms and ecosystems in geographic space and through geological time. Bio-geographical models describe the evolution of species (speciation), migration of species (immigration and emigration) between islands, and the extinction of species. This inspiration allows for information sharing between candidate solutions [24, 81].

A candidate solution constitutes an ‘island’, and the habitat characteristic features are called ‘suitability index variables’ (SIV). The fitness of each solution is called ‘habitat suitability index’ (HSI). Islands with high HSI are said to be friendly to life, and they tend to share their features with those with low HSI by emigrating solution features to other habitats. Those with low HSI accept a lot of new features from the high HSI solutions by immigration from other habitats. This process improves the solutions and evolves a solution to the optimisation problem.

Migration and mutation are the two main operators of BBO. Mutation increases the diversity of the population to evolve better solutions. A remarkable feature of BBO is that the original population is not discarded after each generation, but modified by migration. The immigration and emigration rates are determined by the fitness of each solution. BBO has successfully been applied to solving both static and dynamic ELD problems, deregulated system, and voltage stability/security [82-84, 85].

2.2.7 Simulated Annealing

Simulated Annealing (SA) is based on thermodynamics and metallurgy, inspired by the formation of crystals in solids during cooling, in order to increase the sizes of the crystals and reduce unwanted defects. Developed differently by Kirkpatrick *et al*, in 1983 [86], and Cerny in 1985 [87], SA was introduced to solve complex optimisation problems. Optimal solution results from a careful choice of cost function, appropriate mutation mechanism, solution space and cooling process. General/implementation simplicity, ability to deal with arbitrary cost functions and to refine optimal solutions necessitates its applicability. However, its major drawback is repeated annealing [4, 9], leading to high computing time requirement. This can be overcome through parallel processing in a multi-processor system. Applications to power system are in the area of UC, static and dynamic ELD, power bidding in a deregulated system, maintenance scheduling and planning of transmission and distribution expansion [88, 89].

2.2.8 Harmony Search

The Harmony Search (HS) algorithm, proposed in 2001 by Geem *et al* [90], is a new nature-inspired algorithm which mimics the improvisation process of music players to find the perfect state of harmony. Each musician is a decision variable, each note is a value, while the best harmony is a global optimum. The work flow is illustrated in figure 6. Steps to HS algorithm implementation are as follows:

(i) Defining the problem and specifying the parameter values. The parameters are: the harmony memory size/number of solution vectors in the harmony memory, harmony memory considering rate, pitch adjusting rate, and the number of improvisations (stopping criterion);

(ii) Initializing the harmony memory, generated uniformly within a given range (lower and upper bounds of each decision variable);

(iii) Generating a new harmony, called ‘improvisation’, using the following rules: memory consideration, pitch adjustment, and random selection;

(iv) Updating the harmony memory – the generated harmony vector replaces the worst harmony in the harmony memory if its fitness is better than the worst harmony;

(v) If the stopping criterion is met (number of iterations is reached), the computation is terminated, otherwise, steps (iii) and (iv) are repeated.

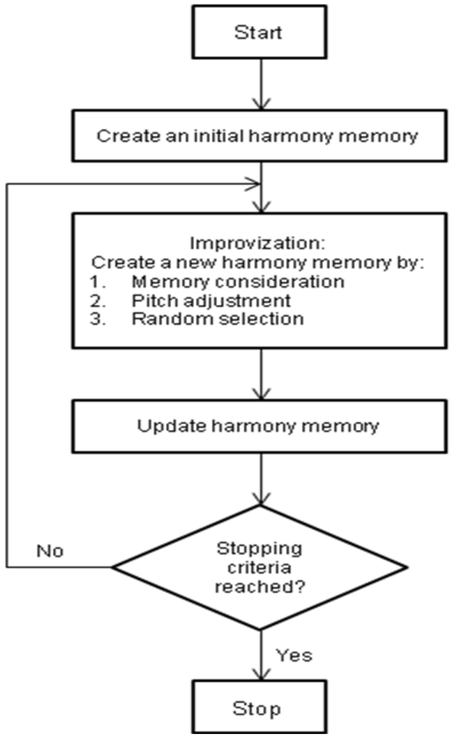

Figure 6. A work flow illustration of harmony search

HS has successfully been applied to solving power system optimisation problems such as: smooth and non-smooth cost functions UC and static, dynamic ELD, including deregulated environments [91, 92, 93, 94].

2.3 Hybrid Methods

Practical modern and real life power systems problems are characterized by non-convex cost functions and non-linearity of generators outputs, such as ramp rate limits, prohibited zones and complicated constraints. These characteristics render the problems very challenging for any optimisation algorithm, as it may not be able to find an optimal solution in good computational time for larger systems. This challenge has led to the exploration of hybrid methods in this application domain. A hybrid method integrates two or more optimisation techniques in attempt to combine their strengths and overcome any inherent weaknesses in either of them.

In [95], PSO was combined with SA to create an innovative approach capable of generating high quality solutions with greater stability in convergence characteristics and reduced calculation time. This is as a result of PSO's major problem of premature convergence, where the particles readily fly into local optima, and SA has a high probabilistic jumping feature for helping to overcome the PSO's major weakness. The work proposed a new coding scheme, which involved normalizing the current generator's output based on the previous output, and then rearranging the ramp boundaries to consider the limits.

In [96], an approach was proposed for solving the combined economic and emission dispatch (CEED) problem using a binary coded GA and PSO. The CEED was converted into a single objective function using modified price penalty factor approach, and applied in the areas of UC, ELD and power distribution.

In [97], a GA was hybridized with FL (fuzzy cardinal priority ranking), where a Pareto optimal solution for the multi-objective generation and emission dispatch problem involving different combinations of fuel cost, oxides of nitrogen, sulphur and carbon, was solved using a non-dominated sorting genetic algorithm (NSGA-II). The approach uses a crowding distance technique to add diversity to the converging solutions, elitist strategy to preserve the best solution in a current population, and NSGA II to provide solutions very close to Pareto-optimal. The result is a single best compromise solution of all the required objectives (reduction of fuel cost and gaseous emissions). It was tested with a system of 6 generators. The approach has been applied in ELD, power system control, and power stability.

In [98], a hybrid method of GA and Lambda iteration was used to economically determine the output of power generators with prohibited operating zones. The approach involved two steps. The first step uses lambda iteration method without considering prohibited operating zones, while the second step uses GA process any units that are caught within prohibited operating zones, by setting their limits to either the lower or upper limits of the prohibited zones.

In [48], GA was combined with DE and SQP to overcome premature convergence and speed up the search process for ELD with valve-point loading effects. The algorithm consisted of two parts: the first part uses a GA to find a near-optimal global search region, while the second part uses DE to explore the search region and SQP to exploit (find tune) the solutions in order to locate local optimum solutions.

In [99], GA was hybridized with Pattern Search (PS) and SQP to overcome the drawback of PS and SQP methods that need to be supplied with initial/suitable starting point by the user. Relying on these good guesses at the initial points makes the methods more likely to get trapped in local optima. Here, the GA generates the initial good solution automatically. PS was used with SQP to refine or fine tune the search.

3. COMPARATIVE ANALYSIS AND DISCUSSION

The computational approaches have the ability of finding global optimal or near-optimal solutions to power systems optimisation problems, though, most of them suffer from long computation time requirements and a large number of problem-specific parameters. Table 2 summarises the different types of approaches used for solving different types of power system problems. Most common application areas are unit commitment; economic load dispatch; transmission, and distribution network expansion planning; load and price bidding transactions in a deregulated system. Table 2 shows that Evolutionary Algorithm (EA) and Artificial Neural Network (ANN) are the most widely used computational intelligence approaches for solving power system problems. Although ANN has ability to learn/adapt to training data, and it is appropriate for solving non-linear power system problems, but the problem with this approach (and virtually all the other machine learning approaches) is that for large-scale problems, several layers/nodes are involved, which requires many parameters. Much longer time is required for training, and optimal results are not guaranteed. This is why attention is currently given more to using EA in solving large-scale power problems. Genetic Algorithm (GA) is the basis of all other EAs. Genetic Programming (GP) is a specialization of GA, but each individual is a computer program (represented as a function tree) that performs a user-defined task. Evolutionary Programming (EP) is similar to GP, but the structure of the programs is fixed, whereas the parameters gradually evolve. Evolutionary Strategy (ES) and Differential Evolution (DE) do not implement crossover. They have fewer control parameters and mainly rely on mutation to achieve their solutions. DE is easy to implement as it requires fewer parameter tuning, converges faster, is reliable and accurate, but due to the greedy nature, noise may affect its performance. Estimation of Distribution Algorithm (EDA) builds probabilistic models to prevent disruption of solutions as they move from across generations, but its results are only ‘estimates’.

There exist some similarities between EAs and Swarm Intelligence (SI) approaches: they start by initializing their solutions, which are updated across generations. But while EAs have evolution operators, particles in SI, especially Particle Swarm Optimisation (PSO) attain optimum by following the current global optimum. PSO maintains more diversity in its solutions than EAs [24].

In a direct analogy to human process, Artificial Immune System (AIS) adopts learning, memory and retrieval system to solve recognition, classification and optimisation tasks involved in electrical power problems. The simplicity, robustness and fastness of Shuffled Frog Leaping Algorithm (SFLA) makes it very efficient in calculating the global optima of many problems with large search space, including finding high quality solutions to complex power problems. The producer-scrounger model of Group Search Optimizer (GSO) is simplified for accuracy and ease of computation by assuming only one producer with several scroungers and rangers at each search point. A remarkable feature of Biogeography-Based Optimisation (BBO) is that the original population is not discarded after each generation, but modified by migration. Simulated Annealing is advantageous in that, it does not need a complex mathematical model of the optimisation problem, it has a faster convergence, and low memory requirements. However, the major disadvantage is the high computing time requirement, arising from repeated annealing process.

Table 2. Electrical power system problem types and applicable solution approaches

S/No	*Electrical Power System Problems Types*	*Applicable Approaches*
1	Load monitoring and forecasting	Artificial Neural Network, Fuzzy Logic, Support Vector Machine
2	Voltage stability/security	Artificial Neural Network, Differential Evolution, Particle Swarm Optimisation , Artificial Immune System, Shuffled Frog Leaping Algorithm, Biogeography-Based Optimisation , Harmony Search, Support Vector Machine
3	Unit commitment	Artificial Neural Network, Genetic Algorithm, Evolutionary Programming, Evolutionary Strategy, Differential Evolution, Estimation of Distribution Algorithm, Ant Colony Optimisation , Particle Swarm Optimisation , Bee Colony Optimisation , Artificial Immune System, Shuffled Frog Leaping Algorithm, Group Search Optimizer, Biogeography-Based Optimisation , Simulated Annealing, Harmony Search
4	Economic load dispatch	Artificial Neural Network, Genetic Algorithm, Evolutionary Programming, Evolutionary Strategy, Differential Evolution, Estimation of Distribution Algorithm, Ant Colony Optimisation , Particle Swarm Optimisation , Bee Colony Optimisation , Artificial Immune System, Shuffled Frog Leaping Algorithm, Group Search Optimizer, Biogeography-Based Optimisation , Simulated Annealing, Harmony Search, Genetic Programming

5	Fault diagnosis and protection	Artificial Neural Network, Fuzzy Logic, Expert System, Bayesian Network, Artificial Immune System
6	Security assessment	Artificial Neural Network, Genetic Algorithm, Particle Swarm Optimisation , Artificial Immune System
7	Real power dispatch, stability and control	Artificial Neural Network, Fuzzy Logic, Genetic Algorithm, Differential Evolution, Particle Swarm Optimisation , Group Search Optimizer,
8	Power system protection	Fuzzy Logic, Expert System, Harmony Search
9	Operation and Planning	Genetic Programming
10	Voltage and reactive power control	Fuzzy Logic, Expert System, Evolutionary Programming, Support Vector Machine
11	Power, transmission and distribution expansion planning	Expert System, Genetic Algorithm, Differential Evolution, Shuffled Frog Leaping Algorithm, Group Search Optimizer, Particle Swarm Optimisation , Ant Colony Optimisation , Evolutionary Programming, Evolutionary Strategy, Simulated Annealing,
12	Load, bid and price transaction (deregulated market)	Expert System, Genetic Algorithm, Differential Evolution, Particle Swarm Optimisation , Artificial Immune System, Evolutionary Programming, Simulated Annealing, Bee Colony Optimisation
13	Alarm processing	Expert System
14	Hydrothermal scheduling	Genetic Algorithm, Evolutionary Programming, Estimation of Distribution Algorithm, Particle Swarm Optimisation
15	Electrical power controller design	Genetic Algorithm, Estimation of Distribution Algorithm
16	Transmission network design, including FACTS devices	Evolutionary Strategy, Ant Colony Optimisation , Artificial Immune System, Shuffled Frog Leaping Algorithm, Group Search Optimizer
17	Maintenance Scheduling	Genetic Programming, Simulated Annealing

4. CONCLUSION

Computational intelligence approaches are actively used optimisation tools among researchers and academics in solving real-world engineering problems, including those in the electrical power industry. This paper surveyed the extent of work that has been done using various the methodologies of computational intelligence, in realising optimal and robust solutions to electrical power systems problems. Their potential application areas were also identified. As seen in Table 2, a remarkable contribution of this work is the provision of a snap-shot guide to researchers and experimentalists on the choice appropriate approach(es) to apply to respective problems they are solving. Several variants of these approaches have been identified to suit the respective problems. One common problem with most of the approaches, especially EAs and SIs is that they are population-based search methods, with random control parameters, and where the number of the search variables are large and highly correlated, realizing global optimal solutions becomes a problem due to the large dimensionality of the dispatch. This is particularly in the case of dynamic unit commitment (UC) and dynamic economic load dispatch problems ELD.

Despite the advances in these emerging solution approaches, there are still potential areas for further study. The introduction of hybrid methods is a novel approach that is yet to be fully and exhaustively harnessed in the electrical power industry to meet the daily increase in the world's energy demands. Arising from the comparative discussion on the approaches, it is evident that integrating two or more of the approaches, combines their strengths and overcome any inherent weaknesses in either of them, giving rise to hybrid methods.

In recent years, there has being a growing interest in the application of Memetic Algorithms (MA) to power systems optimisation. MA results from a combination population-based global search algorithm with an evolutionary framework, and one or more heuristic local search algorithms. The local search algorithms are activated within an iteration of the global search algorithms. MAs have successfully been used to solve a range of electrical power systems optimisation problems, including ELD, UC, planning and scheduling of transmission and distribution system networks, control of reactive power, etc. In comparison with other search methods that have classically been used for such problems, MAs tend to find good solutions in relatively shorter time. However, the literature of MA applications in this area reveals that many different algorithms have been explored – Artificial immune System (AIS), Shuffled Frog Leaping Algorithm (SFLA), Group Search Optimizer (GSO) and Biogeography-Based Optimisation (BBO), but there have been no attempts to design variants of all these approaches that are intelligently tailored to the specific features of power system problems, particularly UC and ELD problems. It is therefore recommended that current and future work in this area concentrate more on investigating variations of these approaches that are tailored to specific power system optimisation problems.

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