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Application of Cuckoo Search Algorithms to South African Short-Term Electricity Load Forecasting

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Abstract

Cuckoo search is one of nature-inspired algorithms successfully used for solving different optimisation problems. Cuckoo search has proved to be very effective than other nature-inspired algorithms. In this paper, a back propagation neural networks configuration is used for South African short-term electricity load forecasting. Cuckoo search algorithm was used to overcome limitations of back propagation. Nine inputs were used to train the neural networks for each of various Cuckoo search algorithms. The first set of results confirmed that Cuckoo search algorithm whose random walk step sizes were derived from Gamma probability distribution out performed other probability based cuckoo search algorithm. It obtained mean average percentage error of 5.6% and Pareto based Cuckoo search obtained 5.8%, while the original Levy based Cuckoo search algorithm performed worse with mean average percentage error of 8.4%. The second set of results confirmed that Cuckoo search with linear decreasing switching parameter outperformed other dynamic changing switching parameter cuckoo search algorithm with mean average percentage error of 6.2% followed by cuckoo search with exponentially increasing switching parameter with mean average percentage error of 6.7%.

Keywords

Optimisation, Nature-Inspired Algorithms, Cuckoo Search, Probability Distribution, Neural Networks, Back Propagation

1. Introduction

Optimisation is a systematic process of determining the optimal solution to a given problem [1]. This process either solves for a minimum or a maximum value of a problem, known as an objective function or cost function. Optimisation problems can be classified into constrained or unconstrained problems. Constrained optimisation problems apply when solution/s being solved are constrained to a subset of all practical solutions, while unconstrained optimisation problems solutions span across all viable solutions set [2], [3]. Optimisation plays a significant role in solving different engineering problems including but not limited to systems design, electricity network operation, electricity generation, wireless communications routing and minimisation of energy losses during electricity transmission. Proper validations of optimisation algorithms require assessment of computational time and convergence rate in addition to the accuracy to determine the minimum or maximum values [4].

Some researchers have innovated optimisation algorithms based on their observations of some natural behaviours like animals, these algorithms are known as nature-inspired algorithms. In [5] a Bat-inspired algorithm was developed based on echolocation to sense distance between a bat and its surroundings. It is the first nature-inspired algorithm to use frequency tuning (the process of changing hearing frequency) so that they can identify objects around them accurately. Particle Swarm Optimisation (PSO) was innovated after observing the behaviour of animals that do not have leaders like fish and birds schooling while searching for food (potential solution) [6]. Each animal member searches for food randomly and communicates to the rest of the group when it's close to the food source. Processing of communication from all other group members is used to determine the best food source (solution). Differential Evolution (DE) algorithm was created by Storm and Prince [7], based on population vectors. The vectors are chosen according to uniform probability distribution and the size of the population does not change during the search process. The population growth is based on mutation (generation new vector), crossover (increasing the diversity of new vectors) and selection (decision to determine if the new member not be part of the population or not) operations. DE is used for continuous space and efficient and robust [8]. Ant and Bee algorithms were developed based on the foraging behaviour of ants and bees that use pheromone as a chemical messenger and the concentration of pheromone is regarded as an indication of quality solutions to the problem being solved [9]. Simulated Annealing (SA) is probabilistic nature-inspired algorithm often used in discrete global optimisation. It is preferred when determining an approximation global solution is important than the find an actual global solution due to limited time constraints [10].

Genetic Algorithm (GA) is about the process of generating offspring from parent solutions using three key operations. Crossover operation helps to exploit and enhance convergence to correct solution. Mutation deals with exploitation and less exploration. Selection guarantees that the correct solution remains part of the population [11]. The GA can converge easily to global optimality.

Cuckoo Search (CS) algorithm is also a nature-inspired algorithm, based on brood reproductive strategy of cuckoo birds to increase their population [11]. However, CS is more effective than other nature-inspired algorithms. In fact, DE, SA and PSO are exceptional cases of CS algorithm, hence it is not a surprise why CS algorithm outperforms them [11]. In [12] CS algorithm outperformed DE algorithm in terms of convergence speed to reach the optimum solution. In addition, CS algorithm was reported as being more computationally efficient than the PSO [13].

Another interesting nature-inspired algorithm is Firefly algorithm (FA), based on unique short and rhythmic light flashes produced by fireflies for three reasons. Firstly, the light is used as a form of communication to attract mating partners. Secondly, the flashes are used to attract potential prey and lastly, the flashes are used to remind and repel potential predators since the fireflies have bitter taste [14].

Yang [11] further confirmed that CS algorithm has two distinct advantages over other nature-inspired algorithms like SA and GA; its efficient random walks and balanced between local and global searching.

The CS algorithm has been used to solve optimisation problems across different industries. Baskan [15] used CS algorithm to minimise traffic congestion by improving the performance of transportation road networks. The objective function was defined as a total of travel time and invested the cost of 16 link capacity expansions. Cuckoo Search produced best results when compared to other methods found in the literature. In [16] CS algorithm was used to maintain fault level and the voltage fluctuations within an acceptable level, thus minimise real power losses in a smart grid.

Since it invention, electrical energy and power have played major roles in providing energy to many industries around the world. Electrical energy can be produced from Wind, hydro plants, coal and nuclear sources. Once challenge facing electricity utilities is to have an efficient way of storing this energy such that it is always sufficient when needed by consumers. One approach to handle this challenge is to forecast electricity demand at any given time and produce only the amount of electricity needed.

Short-term load forecasting (STLF) is a process of forecasting electricity for one hour to one-week periods, and it is needed for power planning and power network maintenance [17]. The forecasting provides accurate information required by power utilities to ensure that correct power is generated, transmitted and distributed to consumers at the right time. The load forecasting is important for many reasons. It helps power utilities to plan the operations and maintain power system more efficient. In addition, it minimises the operational risk and enables the power utility to make economic and technical decision in terms of infrastructure investments. Moreover, it empowers power utility to secure required resources like manpower and fuel to produce and supply power to consumers. Furthermore, it can help power utility to manage its budgeting and cash flow more accurately [18].

It is important to understand factors that affect load forecasting especially short-term load forecasting, Singh et al [19]. These factors include but not limited to the following. Time factor [20], load demand is not uniform throughout a day, for example, in the morning the load demand can be high due to geysers being switched on and some consumers prepare breakfast. During the days, the electricity demand is lower than in the morning or evening because people are at work. Weather factors like wind speed and direction, rain, cloud cover, temperature and humidity in the air can influence usage of electrical appliances like heaters and air conditions. [21]. Singh et al [19] argued that price factor has a direct relationship to electricity load. This might be true for price-sensitive consumers who might start using less electricity to due to high electricity price.

The rest of this paper is organised as follows: Section 2 introduces the cuckoo breeding behaviour, levy distribution and CS algorithm. Section 3 discusses the short-term load simulation methodology. The experimental results and discussions are presented in section 4. Finally, section 5 concludes the paper.

2. Literature Review

2.1. Neural Networks

Neural Networks (NN) method is derived from modelling of human brains which comprises many interconnected neurons. The weights between neurons are changed during learning and thus able to solve non-linear complex problems [22].

To supply high-quality electricity energy, it is important to overcome both financial and technical challenges facing electric power utilities [23-25]. An integrated neural network (NN) has been encouraged for STLF especially when used with temperature values. Furthermore, temperature profiles improved the NN results for STLF by 60% [26], the heat index also improves load forecasting results [27]. Moreover, NN possesses fast learning capability [28], and some scholars consider NN better than traditional regression-based methods [29]. However, statistical methods can complement NN methods in STLF like in the case of forecasting 1 to 24 hours ahead load demand [30]. Marin *et al.* [31] described a global NN-based model for STLF 24 hourly values for the next day for years 1989 to 1999, Spanish data confirmed that the model is more accurate than statistical methods.

On the contrary, too many temperature sources like in North America can impose some challenges with respect to which values to use and how since the country is large with different temperatures. Fan *et al.* [32] implemented a way of combining the weather information using adaptive coefficients and obtained 25% hourly forecasting better than normal NN. Similarly, De Felice and Yao [33] introduced ensembles NN and used it for load forecasting in Rome, Italy. One issue with temperature values for STLF is the forecasting errors that occur when the season's change and load demands are less predictable. These errors can be reduced by implementing a moving data window algorithm to train multistage NN system. In [34], this forecasting method achieved hour-ahead and day-ahead forecasts within 2% and 5%, respectively.

In the same manner, the learning process of NN also depends on the number of hidden layers [35]. The modified general neural networks (GRNN) algorithm can reduce the number of NN inputs. The GRNN method was tested using part of 2007 and 2008 part of nine New Zealand electrical substation loads. Despite minor errors in forecasting daily peak values, the method was fast and able to work in real-time operation [36].

Similarly, the accuracy and computational speed of NN in STLF depends on the learning algorithm used. In [37] the back-propagation (BP) tendency of being trapped in a local minimum point (solution) was managed by applying genetic algorithm-based BP NN on 2010 to 2011 Fuzhou data. The particle swarm optimisation (PSO) used to train NN and yield the mean absolute percentage error (MAPE) of 1.9882% compared to BP-based NN with MAPE of 3.5164% [38]. GA-based NN produced training and forecasting errors of 9.51% and 13.18%, respectively. While the traditional NN produced higher traditional and forecasting errors of 12.12% and 14.31%, respectively [39]. Another GA based training algorithm was used in Mazandaran area in Iran for hourly load forecasting, maximum MAPE of 9.36%, more efficient than normal NN implementation with maximum MAPE of 10.19% was produced [40]. The echo state networks and principal component analysis based NN could forecast 10 minutes and 1 day ahead for Rome power grid [41].

It is important to realise that many studies have been dedicated to improving the training algorithms for NN. Firstly, Amjady [42] introduced forecast aided state estimator to train NN and forecast loads for holidays in Iran and again he and other scholars applied evolution algorithm to NN for handling STLF for the microgrids [43]. Secondly, the Bayesian and SVM learning methods for NN training results were slightly better than the NN STLF [44]. Thirdly, extreme learning machines algorithm reached accuracy with MAPE of 1.82% while BP NN obtained MAPE of 2.93% and the training computational time was reduced from 28.7 seconds to 1.06 seconds in the Australian National Electricity Market [45].

2.2. Cuckoo Search Algorithm

Cuckoo Search algorithm is one of latest metaheuristic nature-inspired algorithms. It is used to solve many engineering and non-engineering optimisation problems across different fields.

2.2.1. Original Cuckoo Search

Cuckoos are a family of birds with unique reproductive strategy more aggressive compared to other bird's species. To increase the hatching probability of their eggs, they use brood parasitism method of laying their eggs in other bird's nests or host nests [46].

Their timing of laying the eggs is very precise. The parasitic cuckoos are good in sporting nests where eggs have just been laid. They lay one egg in the host nest which will normally hatch quicker than the other eggs. When this happens, the foreign cuckoo would remove the unhatched eggs from the nest by pushing the eggs out of the nest. This behaviour is aimed at reducing the probability of the legitimate eggs from hatching. Secondly, the cuckoo chick increases its chances of a good supply of food. Furthermore, the foreign cuckoo chick can gain access to more food by mimicking the call of the host chicks [46].

There are times when the host cuckoo discovers that one of the eggs is foreign. In that case, the cuckoo either gets rid of the egg or abandon the nest altogether, moves to build a new nest somewhere else. Original Cuckoo Search random walk sted sizes are determined from Lévy distribution. Lévy distribution is defined by equation 1.

$$L(s,\gamma,\mu) = \sqrt{\frac{\gamma}{2\pi}}\exp\left[-\frac{\gamma}{2(s-\mu)}\right]\frac{1}{(s-\mu)^{\frac{3}{2}}}, \tag{1}$$

Where $0< \mu< s< \infty$, μ is a minimum step and γ is a scale parameter.

In Fourier transform, Lévy distribution is defined as

$$F(k) = \exp[-\alpha|k|^{\beta}, 0 < \beta \leq 2 \tag{2}$$

Lévy flights are random walks whose direction is random and its step length is derived from the Lévy distribution [46]. These Lévy flights are performed by animals and insects and it is characterised by series of straight flights followed by sudden 90^{o} turns

2.2.2. Cuckoo Search Algorithm Implementation

CS algorithm is a nature-inspired algorithm developed by Xin-She Yang and Suash Deb in 2009 [47] based on the reproduction of Cuckoos birds. While working with Cuckoo Search algorithms, it is important to associate potential solutions with cuckoo eggs. Cuckoos normally lay their fertilised eggs in other cuckoos' nests with the hope of their off-springs being raised by proxy parents. There are times when the cuckoos discover that the eggs in their nests do not belong to them, in those cases, the foreign eggs are either thrown out of the nests or the whole nests are abandoned. The CS optimisation algorithm is basically based on the following three rules: Each cuckoo selects a nest randomly and lays one egg in it, the best nests with the high quality of eggs will carry to the next generation. For a fixed number of nests, a host cuckoo can discover a foreign egg with a probability $p_a \epsilon$ [0,1]. In this case, the host cuckoo can either throw the egg away or abandon the nest.

CS algorithm is enhanced by using Lévy flight rather than simple isotropic random walk. It maintains a balance between local random walk and the global random walk, controlled by a switching parameter $p_a \epsilon [0,1]$.

```
Objective function f(x), x = (x_1, x_2 ... x_d)^T
Generate initial population of n hosts nests x_i (i=1,2…n)
While (t < Max Generation) or (stop criteria)
   Get a cuckoo randomly by Lévy distribution
   Chose a nest among n (say j) randomly
      If ( F_i > F_j )
         Replace j with the new solution
      End
   A fraction of (P_a ) of worse nests are abandoned and new
   ones are build
   Keep the best solutions (or nests with quality solutions)
   Rank the solutions and find the current best
End while
Post processing
```

Figure 1. *Cuckoo Search Pseudo Code for a Global Minimum Problem.*

2.2.3. Applications of Cuckoo Search

Cuckoo Search algorithms have been used to solve many optimisation problems as a proof that the algorithm is generally more effective than other nature-inspired algorithms. This subsection highlights some of the studies which applied Cuckoo Search algorithm to solve some optimisation problems.

Firstly, the algorithms have been used in speech recognition applications by Sood and Kaur [48]. Secondly, Raviteja et al [49] applied Cuckoo Search to determine complex weights of antenna array elements. They obtained better beam forming properties and reduced side lobes levels when compared with other methods of calculating complex weights. Moreover, another application of Cuckoo Search algorithm in antenna array was carried out to suppress side lobe in a linear antenna array [50]. Thirdly, more studies confirmed that Cuckoo Search optimisation algorithm outperformed other methods in resources scheduling in cloud computing [51]. Fourthly, in the field of image processing, the Cuckoo Search algorithm has successfully been used for image enhancement [52]. Fifthly, Chitra and Ravichandran [53], used Cuckoo Search to solve a unit-commitment problem which included power production cost, generation cost, shut down and start-up costs. The Cuckoo Search algorithm took fewer iterations and total fuel costs were less compared to Shuffled frog leap algorithm. Lastly, in the case of outer space, Cuckoo Search algorithm managed to determine the age and relative contribution of different stellar populations and galaxies. The results from the study strongly confirmed the effectiveness of Cuckoo Search algorithm in space optimisation problems [54].

2.2.4. General Cuckoo Search Improvement

The original Cuckoo Search used fixed values of α, positive step size scaling factor, relates to the scales of the problem to be solved and parameter $p_a \epsilon [0,1]$ used to maintain a balance between local random walk and the global random walk. However, Tusiy et al. [55], proposed an improved Cuckoo Search that uses dynamically changing α and p_a with the number of iterations.

Another study on improving the performance of Cuckoo Search was carried out by Li and Yin [56] who managed to maintain a balance between local and global search using self-adaptive Cuckoo Search. This method involved two search rules based on the rand individuals and the best individuals which are combined with a linear decreasing probability rule. The diversity of the population based on the relative success ratio of the two new parameters is enhanced by introducing a self-adaptive parameter. When tested on 16 benchmark functions, the new Cuckoo Search outperformed the original Cuckoo Search algorithm. Furthermore, the new Cuckoo Search algorithms proved to be very effective when used to determine the parameters of Lorentz and Chen systems.

Cuckoo Search algorithm contribution by Mareli and Twala [57] involve development and testing of three Cuckoo search algorithms based on the linear increasing, power increasing and exponential increasing switching parameters between local and global random walks.

Walton et al. [58] was further improved by Nasa-Ngiun et al. [59], using a pure Lévy distribution for local search and secondly by using chaotic sequences rather than the inverse gold ratio. The Lévy distribution and chaotic sequences are effective for searching uni-modal and multi-modal test functions, respectively. The combination of Lévy distribution and chaotic sequences contribute to the wide range of optimisation problems. This algorithm outperformed the Cuckoo Search algorithm when tested on 19 test functions.

2.2.5. Cuckoo Search Improvement by Probability Distribution Functions

The first study (in 2012) carried out to improve the Cuckoo Search algorithm using different probability distribution was done by Zheng and Zhou [60] who replaced Lévy distribution by Gauss distribution. When applied to find global minimum values of 6 mathematics test functions, the Gauss Cuckoo Search performed better than the Lévy Cuckoo Search for all cases. Furthermore, the Gauss Cuckoo Search algorithm was used to solve engineering design optimisation problem. The results still confirmed that Gauss Cuckoo Search is better than the Lévy Cuckoo Search in terms of higher convergence rate and the average generation was reduced from 20.15 to 13.95.

The rapid growth rate of documentation in the Internet space poses some challenges, especially in the documentation retrievals process. Zaw and Mon [61], solved this web document clustering by using a Gauss based Cuckoo Search algorithm. The algorithm was tested on 3 clusters and 300 documents. The results confirmed that Gauss Cuckoo Search algorithm outperformed Lévy Cuckoo Search algorithm. More specifically, the convergence rate of Gauss Cuckoo Search and Lévy Cuckoo Search are 120 and 160 iterations, respectively. The quality of clustering was determined by a combination of Precision and Recall, called F-measure where high F-measure indicate high accuracy. The Gamma Cuckoo Search algorithm and Lévy Cuckoo Search algorithm produced F-measure of 0.626 and 0.619, respectively.

In 2014, Ho et al. [62] modified Cuckoo Search by using Gaussian and Cauchy distributions and applied them to solve economic emission load dispatch problem with multiple fuel options. The new versions of Cuckoo Search algorithms resulted in fewer parameters, fewer equations and shorter computational processes when compared to Lévy Cuckoo Search. In addition, the Gauss Cuckoo Search performed better than the Cauchy Cuckoo Search algorithm. The application of Gauss Cuckoo Search and Cauchy Cuckoo Search for short-term hydrothermal scheduling with reservoir volume constraint was done by Nguyen et al. [63]. In this study, however, Lévy Cuckoo Search produced the best results with the lowest minimum compared to Gauss and Cauchy Cuckoo Search algorithms. Furthermore, the Gauss Cuckoo Search algorithm average time was 1.47% more than the Lévy Cuckoo Search algorithm average time. While the Cauchy Cuckoo Search algorithm average time was 4.83% more than that of Lévy Cuckoo Search algorithm.

Roy et al. [64] managed to improve Cuckoo Search by using Gamma distribution instead of original Lévy distribution. When tested on 6 mathematical test functions, the Gamma Cuckoo Search proved to be more accurate and efficient than the Lévy Cuckoo Search algorithm. The best performance was recorded for the Ackley test function for 1000 iterations where Lévy and Gamma Cuckoo Search algorithms produced average minimum valves of 1.0923exp (-15) and 2.22507exp (-308), respectively. This study would be more interesting if it was extended to solving an actual engineering problem using Gamma and compare the results to the Lévy Cuckoo Search algorithm. Mareli and Twala [65] improved the original Cuckoo search by deriving random step sizes from Pareto probability distribution. The results were better that that of the original cuckoo search algorithm.

3. STLF Simulations

3.1. Methodology

3.1.1. Data Collection

Two sets of hourly historical data from 2012 to 2015 were obtained to train and validate the neural network model used.

The first data was for electricity in kWh from CityPower. The second set of data was weather parameters from South African Weather Services (SAWS), the units for each parameter can be found in Table 1. Some of the data provided by SAWS has missing hour values. The SAWS attributed the missing valves to communication issues experienced between the weather stations where the data was collected remotely and the main server in the SAWS offices where the data was stored. In such cases, the previous hour values were reused to avoid blank data fields. These occurrences were very few and less than 0.1%, it is believed that they have no significant impact on STLF distortion.

Table 1. *Hourly weather data and units.*

Weather Parameter	Units
Wind speed	meters per second (m/s)
Wind direction	degrees (clockwise)
Temperature	degree Celsius (°C)
Humidity	percentage (%)

3.1.2. Data Pre-processing

Sometimes when large values of inputs are fed into a transfer function, the output is larger than the actual range that can be handled by transfer function output. When that happens, the output values get distorted and the results of the neural networks become unreliable and distorted. To prevent such issues, neural networks are normally normalized and in this case, the data output was normalised to (+1, -1) using a mapminmax function in MATLAB. Also, any missing value in the data was made same as the previous value.

3.2. Simulations Setup

Figure 2 shows feed-forward neural network used in STLF. It has 9 input variables which are explained in Table 2. The network has 20 neurons in the hidden layer using sigmoid as a transfer function. The output layer has one neuron with linear output function.

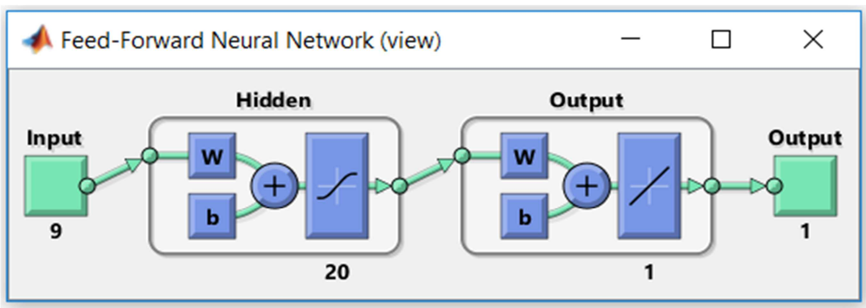

Figure 2. *Feed-Forward Neural Network with Levenberg-Marquardt Back Propagation.*

Table 2. *Neural Network Input Variables.*

Input	Input Variable Description
1	Previous hour electricity consumption
2	Previous hour humidity
3	Current hour humidity
4	Previous hour wind speed
5	Current hour wind speed
6	Previous hour wind direction
7	Current hour wind direction
8	Previous hour temperature
9	Current hour temperature

The output of neural networks is the forecasted hourly electricity consumption.

The Feed-Forward neural network is trained and forecasts using a hybrid of Levenberg-Marquardt back propagation and Cuckoo search algorithms. The call flow for this hybrid is presented in Figure 3. This hybrid is more efficient than Levenberg -Marquardt BP, since BP alone can get trapped in local minima and fail to find global minima of the loss or test function.

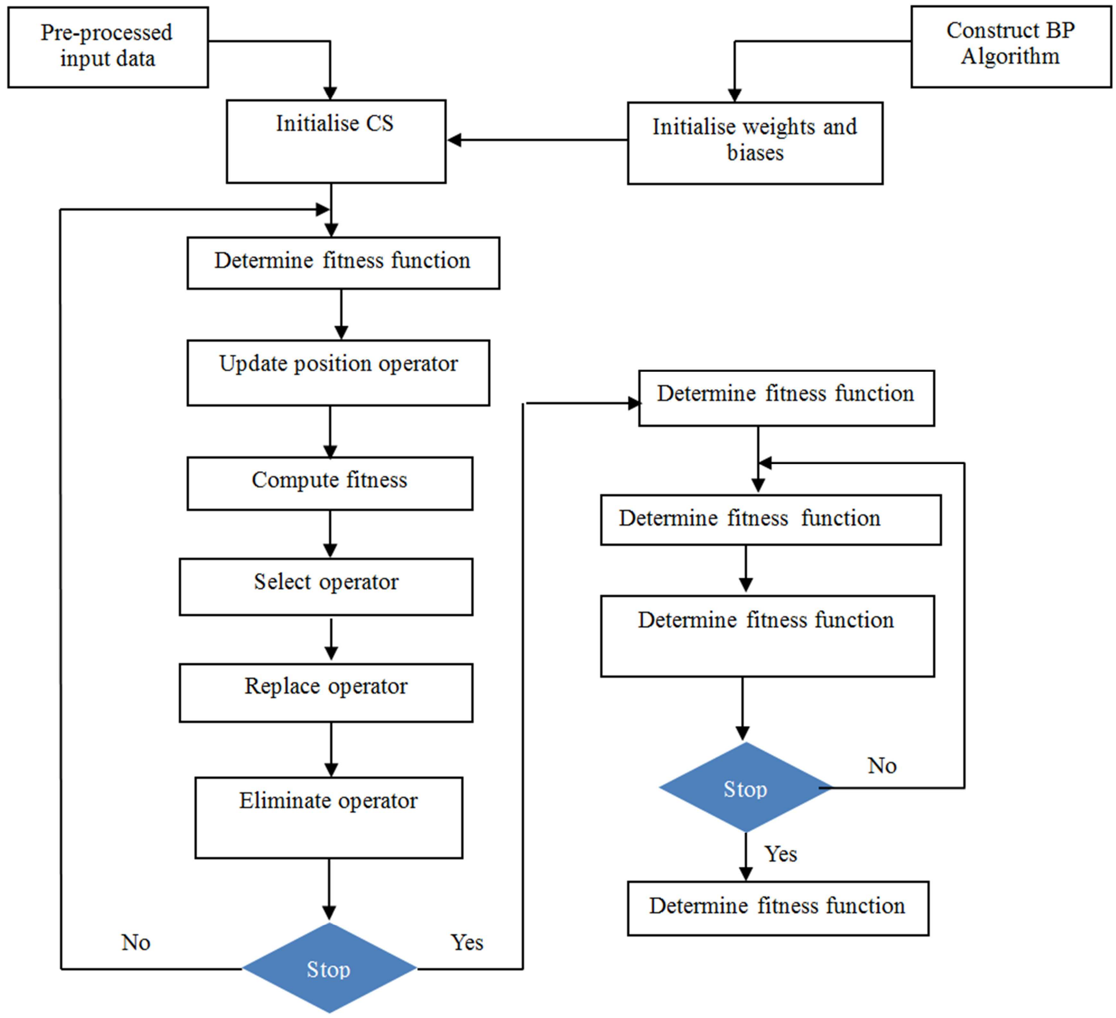

Figure 3. *Optimised Levenberg-Marquardt [66].*

4. Results and Discussions

Electricity load forecasting results for 19th February 2015 are tabulated in Tables 3 and 4, for probability-based CS algorithms and Tables 5 and 6 corresponds to using changing switching parameter CS algorithms.

Form Table 4, the best performing Cuckoo search algorithm is GammaCS with MAPE of 5.6% followed by ParetoCS with MAPE of 5.8%. These results confirm that the Cuckoo search algorithm with random walk step sizes derive from Pareto probability distribution performed better that the original Cuckoo search based on Levy probability distribution. In fact, the Levy based Cuckoo search algorithm was the least performer from five probability based Cuckoo search algorithms.

From Table 6, the best performing Cuckoo search algorithm is the one with linear decreasing switching parameter between local and global random walks (CSLI) with MAPE of 6.2% followed by Cuckoo search with exponentially increasing switching parameter (CSEI) with MAPE of 6.7%. The cuckoo search with power increasing switching parameter also performed better than the original constant switching parameter Cuckoo search algorithm (CSCo).

Table 3. *19th of February 2015 Load Forecasting using probability-based CS algorithms.*

Date and hour	Load (Kwh)	LevyCS	CauchyCS	GaussCS	GammaCS	ParetoCS
2015/02/19 00	6.367	5.8759770	5.9372275	5.8792878	6.03120442	6.01878877
2015/02/19 01	6.364	5.8732083	5.93443	5.8765176	6.02836264	6.01595284
2015/02/19 02	6.968	6.4306278	6.49766	6.4342512	6.60050768	6.58692008
2015/02/19 03	10.757	9.9274202	10.030903	9.9330138	10.1896758	10.1686997
2015/02/19 04	15.698	14.487370	14.638385	14.495533	14.8700874	14.8394764
2015/02/19 05	14.569	13.4454387	13.585592	13.453014	13.8006309	13.7722214
2015/02/19 06	11.321	10.447925	10.556833	10.453811	10.7239305	10.7018545
2015/02/19 07	11.254	10.386092	10.494355	10.391944	10.6604641	10.6385187
2015/02/19 08	11.447	10.564207	10.674328	10.570160	10.8432852	10.8209636
2015/02/19 09	11.262	10.393475	10.501815	10.399331	10.6680421	10.6460812
2015/02/19 10	11.017	10.167369	10.273353	10.173098	10.4359634	10.4144803
2015/02/19 11	10.921	10.078773	10.183832	10.084451	10.3450265	10.3237305
2015/02/19 12	10.928	10.085233	10.19036	10.090915	10.3516573	10.3303477
2015/02/19 13	11.521	10.632501	10.743333	10.638491	10.9133825	10.8909165
2015/02/19 14	12.738	11.75564	11.878185	11.762269	12.0661979	12.0413588
2015/02/19 15	14.615	13.487891	13.628488	13.495491	13.8442049	13.8157057
2015/02/19 16	18.044	16.652447	16.82603	16.661830	17.0923594	17.0571736
2015/02/19 17	21.827	20.1437017	20.353677	20.155051	20.6758440	20.6332814
2015/02/19 18	24.421	22.537653	22.772583	22.550351	23.1330365	23.0854155
2015/02/19 19	20.35	18.780608	18.976375	18.79119	19.276741	19.2370585
2015/02/19 20	14.449	13.334693	13.473693	13.342207	13.6869597	13.6587842
2015/02/19 21	9.687	8.9399386	9.0331275	8.9449758	9.17610762	9.15721797
2015/02/19 22	7.512	6.9326746	7.00494	6.9365808	7.11581712	7.10116872
2015/02/19 23	6.76	6.2386688	6.3037	6.242184	6.4034776	6.3902956

Table 4. *Mean Absolute Percentage Errors (MAPE) for probability based Cuckoo Search algorithms.*

CS Algorithm	LévyCS	CauchyCS	GaussCS	GammaCS	ParetoCS
MAPE	8.4%	7.2%	8.3%	5.6%	5.8%

Table 5. *19th of February 2015 Load Forecasting using changing switching parameter CS algorithms.*

Date and hour	Load (KWh)	CSCo	CSLD	CSLI	CSPI	CSEI
2015/02/19 00	6.367	5.87597696	5.99351178	5.80231077	5.94728736	5.96931718
2015/02/19 01	6.364	5.87320832	5.99068776	5.79957684	5.94448512	5.96650456
2015/02/19 02	6.968	6.43062784	6.55925712	6.35000808	6.50866944	6.53277872
2015/02/19 03	10.757	9.92742016	10.1259944	9.80296167	10.0478986	10.0851178
2015/02/19 04	15.698	14.4873702	14.7771553	14.3057444	14.6631878	14.7175029
2015/02/19 05	14.569	13.4454387	13.7143825	13.2768754	13.6086115	13.6590203
2015/02/19 06	11.321	10.4479245	10.6569101	10.3169405	10.5747197	10.6138903
2015/02/19 07	11.254	10.38609152	10.5938404	10.2558827	10.5121363	10.5510752
2015/02/19 08	11.447	10.5642073	10.7755190	10.4317656	10.6924138	10.7320204
2015/02/19 09	11.262	10.3934746	10.6013711	10.2631732	10.5196090	10.5585755
2015/02/19 10	11.017	10.16736896	10.37074278	10.0399023	10.2907594	10.3288782
2015/02/19 11	10.921	10.0787725	10.2803741	9.95241651	10.2010877	10.2388743
2015/02/19 12	10.928	10.0852326	10.2869635	9.95879568	10.2076262	10.2454371
2015/02/19 13	11.521	10.6325005	10.8451781	10.4992025	10.7615357	10.8013983
2015/02/19 14	12.738	11.7556454	11.9907889	11.6082667	11.8983110	11.9423845
2015/02/19 15	14.615	13.4878912	13.7576841	13.3187957	13.6515792	13.7021471
2015/02/19 16	18.044	16.6524467	16.9855390	16.4436776	16.8545395	16.9169718
2015/02/19 17	21.827	20.1437018	20.5466282	19.8911634	20.3881642	20.4636856
2015/02/19 18	24.421	22.5376525	22.9884641	22.2551015	22.8111677	22.8956643
2015/02/19 19	20.35	18.780608	19.156269	18.5451585	19.008528	19.078939
2015/02/19 20	14.449	13.3346931	13.6014217	13.1675182	13.4965219	13.5465155
2015/02/19 21	9.687	8.93993856	9.11876058	8.82785997	9.04843296	9.08194998
2015/02/19 22	7.512	6.93267456	7.07134608	6.84576072	7.01680896	7.04280048
2015/02/19 23	6.76	6.2386688	6.3634584	6.1604556	6.3143808	6.3377704

Table 6. *Mean Absolute Percentage Errors (MAPE) for changing switching parameter Cuckoo Search algorithms.*

CS Algorithm	CSCo	CSLD	CSLI	CSPI	CSEI
MAPE	8.4%	6.2%	9.7%	7.1%	6.7%

5. Conclusion

This paper introduced the concept of optimization and highlighted its importance in solving engineering problems. Then different nature-inspired algorithms like Particle Swarm Optimisation, Differential Evolution, Simulated Annealing and Genetic Algorithm were discussed. It was highlighted that Cuckoo search algorithm has efficient random walks and keeps balance between local and global random walks much better than other nature-inspired algorithms.

This paper reviewed some short-term electricity load forecasting using neural networks configurations. The improvement of back propagation using Cuckoo search algorithm was presented. Then the paper went on to discuss some of cuckoo Search algorithm improvements using different probability distribution and dynamic switching parameter. A 9-20-1 feedforward neural networks configuration (9 inputs, 20 hidden-layer and 1 output), used for one-hour electricity load forecasting was present.

The first set of results confirmed that Cuckoo search algorithm whose random walk step sizes were derived from Gamma probability distribution out performed other probability based cuckoo search algorithm. It obtained mean average percentage error of 5.6% and Pareto based Cuckoo search obtained 5.8%, while the original Levy based Cuckoo search algorithm performed worse with mean average percentage error of 8.4%. The second set of results confirmed that Cuckoo search with linear decreasing switching parameter outperformed other dynamic changing switching parameter cuckoo search algorithm with mean average percentage error of 6.2% followed by cuckoo search with exponentially increasing switching parameter with mean average percentage error of 6.7%.

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Conflicts of Interest

The authors confirm that that there is no conflict of interest to declare.

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