OPEN ACCESS

International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Methods in Forecasting Water Used and Electricity Production at Hydropower Plants

Wee Wei Joe, M Y Yuzainee, Nuratiah Zaini, M A Malek

Abstract: ***An energy system in a country has complex impacts on its economy. A retrenchment of energy supply influences economic activity such as distribution and saving of energy, as well as changes in technology to emphasize energy efficiency. Despite the advantages of hydropower developments in power generation over the past decades, highly controversial issues due to various social and environmental concerns are still debatable. A challenge for hydropower developers and operators, as well as government planners and regulators, is to develop tools that promote good practice and sustainable hydropower projects in energy security. In the future, both the scarcity of water and the cost of energy will likely to become limiting factors for economic and population growth, particularly in Malaysia, where the population is projected to grow dramatically. Various climate change models suggested that clean water supplies may decrease significantly. Therefore, integrated planning between the energy and water sectors will be essential to meet the rising demands of both resources. The purpose of this study is to review and identify the method that can deal with historical data and current practices at the hydropower plants to predict future electricity production due to the predicted water used in hydropower plants at the study areas. Various available methods to forecast water used and the electricity generated in hydropower plants have been identified and discussed in this paper.***

Keywords: ***climate change, energy, environmental, hydropower***

I. INTRODUCTION

Malaysia as a growing population country increasingly demands electricity consumption. Electricity consumption is an energy consumption that uses electric energy. One of the main factors in the country's economy is energy production. According to the World Energy Markets Observatory 2017 report, Malaysia's energy usage is projected to increase by 4.8% by 2030 [1]. Global Energy Statistical Yearbook 2018 [2] indicates that total electricity consumption in Malaysia was 51 TWh in 1997 compared to 89 TWh in the year 2007 and 147 TWh in the year 2017. Fig. 1 shows the trend over 1990 – 2017 of electricity consumption in Malaysia. Meanwhile, in 1996, electricity production was 58 TWh compared to 98 TWh in the year 2007 and 166 TWh in 2007.

Fig. 2 shows the trend over 1990 – 2017 of electricity production in Malaysia. Both figures demonstrate an increment of demand for electricity consumption and increment of electricity production. The production of electricity, mainly based on renewable and nonrenewable energy sources. Currently, Malaysia produces 12 % of renewable and 88% nonrenewable energy [2]. Hydropower is the leading renewable source for electricity generation worldwide [3] and it's also one of the world's main energy consumption [1].

At 2018, globally, total installed hydropower capacity has reached 1,267 GW, producing an estimated 4,185 TWh in clean electricity, which comprise two-thirds of all renewable electricity generation [4]. Meanwhile, in 2018, the total installed hydropower capacity; including pump storage in Malaysia has reached 6,094 MW, generating an estimated 17.62 TWh in electricity [4]. Fig. 3 shows the trend over 1990 – 2017 of renewable energy production in Malaysia. The lowest renewable energy production was 5.99% in the year 2010 and the highest production was 17.3% in 1990.

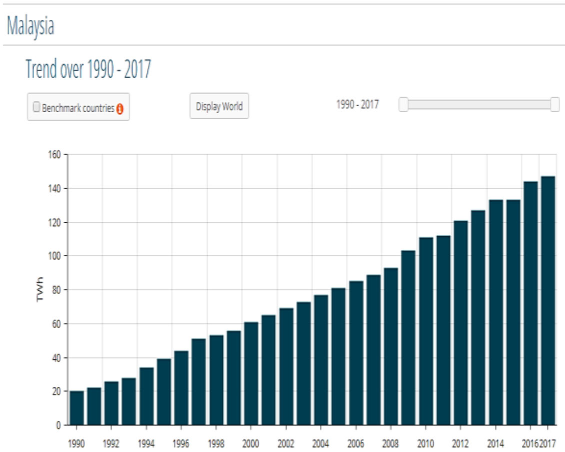

Fig. 1 Trend Over 1990 – 2017 of Electricity Consumption in Malaysia
Source: Global Energy Statistical Yearbook 2018.

Manuscript published on November 30, 2019.
* Correspondence Author
Wee Wei Joe*, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia
M Y Yuzainee, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia.
Nuratiah Zaini, College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia.
M A Malek , College of Engineering, Universiti Tenaga Nasional, Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia.

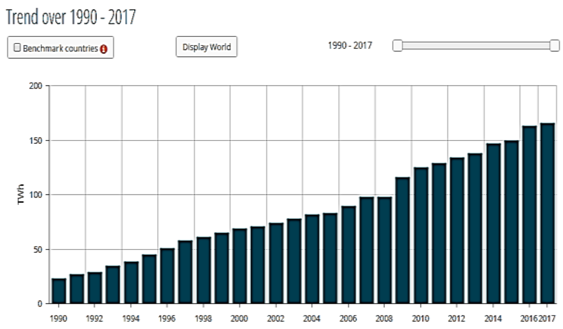

Fig. 2 Trend Over 1990 – 2017 of Electricity Production in Malaysia

Source: Global Energy Statistical Yearbook 2018.

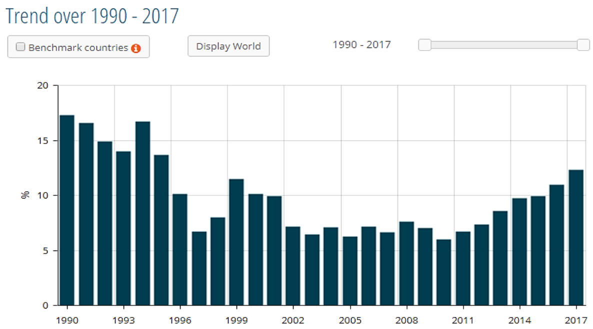

Fig. 3 Trend Over 1990 – 2017 of Renewables Energy Production in Malaysia

Source: Global Energy Statistical Yearbook 2018.

Nowadays, hydropower is the most eminent renewable energy technology [5]. Hydropower harnesses the water-energy moving from higher to lower elevations, primarily to generate electricity and mechanical energy [6, 7]. It uses the gravitational force of water to turn turbines and generate electricity. It builds in various shapes and sizes which depends on the amount and flow of water, from small run-off river facilities to a large reservoir. Currently, there are three types of hydropower facilities: diversion (run-of-the-river or hydrokinetic), impoundment, and pumped storage [7]. This study interest is to discover the methods used in forecasting water used and predicting the electricity generated in hydropower plants. Previous studies revealed various methods to forecast water consumption and electricity generated at hydropower plants. The study aims to determine the best method that can utilize historical data and current practices at the hydropower plants to predict water consumption and energy produced from hydropower plant.

II. METHODS USED TO FORECAST WATER USED AND ENERGY PRODUCED IN HYDROPOWER PLANTS

Water and energy, both become a global main concern. Therefore, hydropower technology has been seen as a twofold solution to the provision of renewable energy and water storage [8]. It provides renewable, low carbon and internal energy beside increases water storage capacity. Various methods have been studied and suggested in previous research in order to forecast water used in hydropower plants. Similarly, several studies have been found on forecasting energy produced in hydropower plants. Following, a discussion of several methods that have been discovered and used in previous studies. The focus of this study is on a method that can utilize historical data and current practices to predict both water consumption for hydrology process and energy produced in the hydropower plant.

A large number of methods to forecast water used in hydropower plants available around the world. At the same time, various methods also available in forecasting the energy produced by hydropower plant. Both, water used and energy produced can use the same method or different methods at the same hydropower plant. This research attempts to study the available methods and select a suitable method for Malaysian contexts. Several methods have been studied which include Topographic Kinematic Approximation and Integration Model (TOPKAPI), Artificial Intelligence (AI) Methods, Artificial Neural Network (ANN), Artificial Bee Colony (ABC) Algorithm and Distributed Generation (DG), Radial Basis Function Neural Network (RBFNN), and Streeter-Phelps (SP) Model. The features on four of those methods are presented as follows.

Topographic Kinematic Approximation and Integration Model (TOPKAPI)

TOPKAPI model is a fully-distributed hydrological model using a physical mechanism with simple in structure and in parameter composition [9, 10] that can apply as a stand-alone program and real-time forecasting in flood operational systems. It simulates the rainfall-runoff transformation using data collected by a network of rain-gauges [11]. TOPKAPI model is one of distributed rainfall-runoff model derived upon the assumption that the horizontal flow at a point in the soil and over the surface can be approximated by means of a kinematic wave model [10]. Consequently, it provides high-resolution information on the hydrological state of a catchment [9]. Spatial distribution of catchment parameters, rainfall input and hydrologic response is achieved horizontally by an orthogonal grid network and vertically by soil layers at each grid pixel [11]. These three structurally similar non-linear reservoir differential equations characterize the TOPKAPI approach and are used to describe components, such as subsurface flow, overland flow and channel flow [11]. Other than these three components, the TOPKAPI model includes evapotranspiration and snowmelt, plus a lake/reservoir component, a parabolic routing component, a groundwater component, infiltration, and percolation as components of the main processes in the hydrologic cycle according to area or location. In the hydrologic cycle, the TOPKAPI model reproduces the operation of these components and computed them separately [11].

The model operates by combining the kinematic approach and the topography of the basin [10, 11] described by means of a lattice of square cells generally increasing in size with the scale of the problem [10]. Each cell (mass balance and the momentum balance) represents a computational node for the physical characteristics of the model. The flow paths and slopes are evaluated from the digital elevation models, according to a neighbourhood relationship based on the principle of minimum energy [10]. As a physical mechanism model, Ciarapica and Todini (2002) pointed out that the values of the model parameters can be obtained from digital elevation maps, soil type and land use maps in terms of topology, slope, soil permeability, soil depth, superficial roughness and slope [10]. A calibration based on streamflow data is used to improve the model to reproduce the behaviour of the catchment. They also explained that the TOPKAPI model can be implemented in ungauged catchments where the model cannot be calibrated using measured data. Thus, the model parameters can be obtained from experience, literature and thematic maps [10].

The advantage of applying the TOPKAPI model is the ability to resolve basin hydrologic response and spatial scales in both small and large catchments, reduced execution times, calibrated the model, predicted flow at any point in the network, exploited spatial variability in precipitation estimates, run the model at different time scales, and run event-based and continuous simulations [10, 11,12]. Furthermore, the model can be used to monitor the catchment during severe hydro-meteorological events and landslide, fire prevention, water resources applications [11]. Meanwhile, the disadvantage of TOPKAPI model is it applicable at rectangular channel geometry only, and artificial redistribution in order to avoid blocked channels for applying TOPKAPI model. It is also limited to steep mountain rivers due to kinematic wave approximation, no counter slopes or backwater effects considered, and limited to bedload transport (no suspended load or wash load) [13]. Despite its limitation, the model can be used to estimate future runoff generation, hydropower production, flood forecasting, catchment hydrology, landslides, land use and climate change, irrigation and drought, water resources management and artificial reservoir management.

a. Artificial Intelligence Methods and Application

Artificial Intelligence (AI) is a branch of computer science that emphases on inventing intelligent machines which work similarly to human beings [14]. AI machines are designed to perform various tasks including learning, perceive, plan, speech recognition, machine vision, process big data and solve problems. These machines are able to perform these tasks with adequate data and knowledge about the world [14]. An AI machine gets knowledge through machine learning using the key aspects of computer science. Cleophas [14] described an AI as a machine with the capability to use its inputs to deduce key aspects of the problem, for example, robotics. AI capability of handling the complex input and output relationship has assisted human beings in solving real-world problems [15]. Lately, the application of AI technology has become a significant tool for hydrological forecasting modeling. The AI tools have been used in numerous hydrologic modelings such as rainfall-runoff modeling, flood forecasting, rainfall prediction, river stage prediction, evaporation estimation, sediment load modeling, water quality simulation and many others. AI techniques are being developed and deployed worldwide as a forecasting tool. For examples, Artificial Neural Networks, Artificial Bee Colony Algorithm, feed-forward neural networks, Radial Basis Function Neural Networks, Multilayer Perceptron Technique, Generalized Regression Neural Network Techniques, Support Vector Regression Method, Deep Neural Network Model and many more.

Artificial Neural Networks (ANN)

An Artificial Neural Networks (ANN) are a computational modeling tool that process information to solve a variety of problems in pattern recognition, prediction, optimization, associative memory and control [16, 17]. ANN has been accepted in many disciplines for modeling complex real-world problems solver [18]. ANN proves to be able to solve complex non-linear input-output relationship that is difficult to other technique. ANN approach is parallel-distributed information processing system to solve problems in the way the brain works [18, 19, 20, 21]. The main structure of ANN is learning adjustment, generality, parallelization, stiffness, stored information and processing information [20, 21]. ANN performance based on the structure of the human brain that imitates brains complexity, non-linear and parallel computer. The basic architecture of ANN usually consists of three layers namely input layer, hidden layer and output layer [18, 19, 20, 21]. The input layer is where the data are introduced to the network. The hidden layer or layers are where data are processed, and the output layer is where the results for given inputs are produced [18, 19, 20, 22]. The architecture is illustrated as in Fig. 4. There are various types of ANN architecture, depending on the number of layers such as a single layer, multilayer, supervised and unsupervised, combined supervised and unsupervised, which is known as Radial Basis Function (RBF) network and temporal ANN [21].

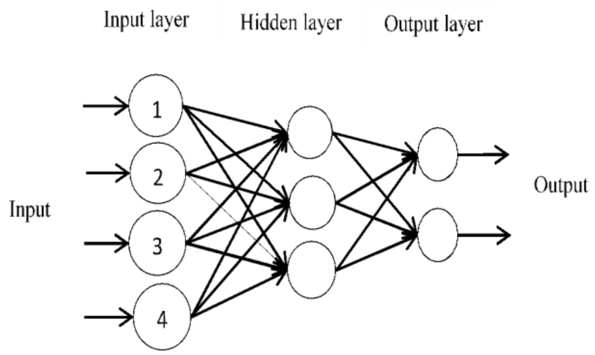

Fig. 4 Architecture of ANN

ANN has the ability to learn, save and make relevance between inputs and outputs. Generally, there are two phases of ANN learning which are training and testing. During the training phase, input data is fed into ANN's architecture with multiple layer and output are computed using random bias and weights. In this phase, the weights are initialized and systematically changed by the learning algorithm. The process is repeatedly presented until the error of predicted data is less than the decided fitness function. However, the process will also be terminated based on the time and iteration number that initially set. This process flow illustrated in Fig. 5. The number of hidden layers depends upon the problem being studied. The disadvantage of ANN process is the possibility to be missed from experiential procedures, particularly if the network has no sufficient degree of freedom to learn the process correctly, or the number of hidden layers is small, and the process may take longer time and tends to overfit the data if the layer is too high. It is always challenging to find the optimum number of hidden layers, however, it can be done by using a trial-and-error method [23, 24, and 25].

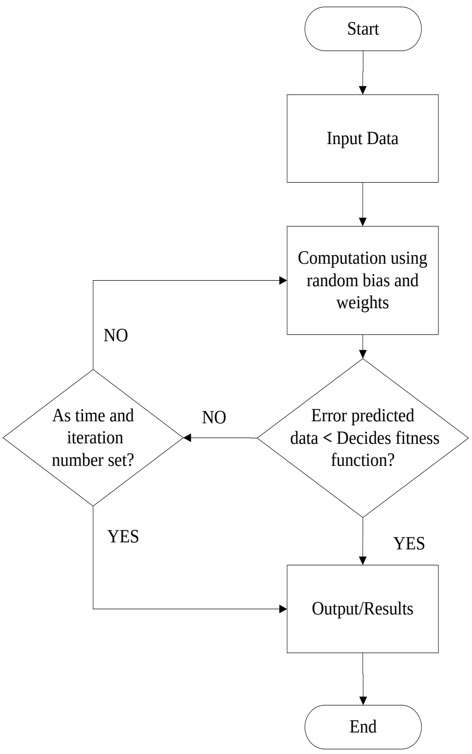

Fig. 5 Training phases of ANN

The advantage of using ANN is its ability to learn fast [17, 18, 20]. It is what makes ANN becomes extremely powerful [17] and useful for a variety of tasks and problems [18, 19, 20]. ANN has learned (trained) through experience with appropriate learning exemplars and not from the programming. It gathered knowledge by detecting the patterns and relationships in data. It gives satisfactory [19] and efficient results [20], thus ANN has been found to have the best performance with regard to input-output function approximation. Due to the ANN flexibility in input-output function approximation, ANN becomes powerful methods in tasks involving pattern classification, estimating continuous variables and forecasting [23]. Therefore, ANN is considered suitable for forecasting water usage and electricity generated in hydropower plants.

b. Artificial Bee Colony (ABC)

An Artificial Bee Colony (ABC) Algorithm is an optimization algorithm based on the intelligent behaviour of honey bee swarm [26]. ABC is an optimization technique based on a metaheuristic algorithm inspired by cooperative foraging behaviours of honey bees [26, 27, 28]. The ABC algorithm is applied to solve various continuous and discrete optimization problems in the areas related to neural networks such as in environmental/ economic problems, network topology design, structural engineering, image processing, forecasting and many others [29]. It solves optimization to discover optimal solutions by foraging process of the honey bee colony. In ABC, food resources denote as an optimal solution and the nectar amount of each resource denote as the quality of each solution. In the ABC algorithm, there are three types of artificial bees groups, namely employed bees, onlookers and scouts [27]. The employed bees comprise the first half of the colony whereas the second half consists of the onlookers. Furthermore, the ABC algorithm has four phases which are initialized, employed bee, onlooker bee and the scout bee [26, 27]. In the initialization phase, ABC starts with a random selection process used by the artificial onlooker bees to discover promising regions which correspond to a potential solution. Second, in employed bee phase, a local selection process carried out by the artificial employed bees and the onlookers in a region depending on the information to determine a neighbour food source around the source in the memory [26]. The employed bees link to particular food sources. In other words, the number of employed bees is equal to the number of food sources for the hive [27, 28]. Next, in the onlooker bee phase, a greedy selection process carried out by all bees [26]. A new candidate solution is produced and the solution is improved in onlooker bee phase by select an employed bee [27, 28]. The onlookers observe the employed bees within the hive, to select a food source, whereas scouts search randomly for new food sources [28, 29]. In the optimal context, the number of food sources in the ABC algorithm is represented to the number of solutions in the population [29]. Similarly, the position of a food source implies the position of a promising solution to the optimization problem. Meanwhile, the quality of nectar of a food source represents the quality of the associated solution [29]. Lastly, in scouts bee phase, a random selection process carried out by scouts' bee [29, 30, 31], the abandonment counters of all employed bees are verified with a predefined limit [26, 27, 28, 30]. Following is the basic step of the ABC algorithm:

1. Randomly initialize the food source positions.

2. Each employed bee is assigned to their food sources.
3. Each onlooker bee selects a food source based on the quality of the solution. Onlooker bee produces a new food source in the selected food source site and exploits a better food source.
4. Decide the source to be abandoned and assign employed by as a scout bee for discovering new food sources.
5. Memorize the best food source found so far.
6. If the requirement is met, output the best solution. Otherwise, repeat steps 2-5 until the stopping criteria are met or maximum iteration is achieved.

Bolaji et al. [29] identified several advantages which ABC holds over other optimization algorithms. These include its simplicity, flexibility, robustness, ease of hybridization with other optimization algorithms, fewer control parameters, ability to handle the objective cost with stochastic nature, ease of implementation, and ease the application of basic mathematical and logical operations [29]. Meanwhile, the disadvantages or limitations of ABC are lack of use of secondary information, requires new fitness tests on new algorithm parameters, a higher number of objective function evaluation, slow when in sequential processing [29].

Bat Algorithm

The Bat Algorithm (BA) is a metaheuristic method developed by Xin-She Yang in 2010, nature inspired by the echolocation behaviour of microbats [32]. A metaheuristic is a higher-level procedure designed to find, generate, or select a heuristic that may provide a good solution to an optimization problem, even though with incomplete or imperfect information or limited computation capacity [33]. The basic steps of the BA have been summarized by Bozorg-Haddad et al. [33] for minimization problems are shown in Fig. 6.

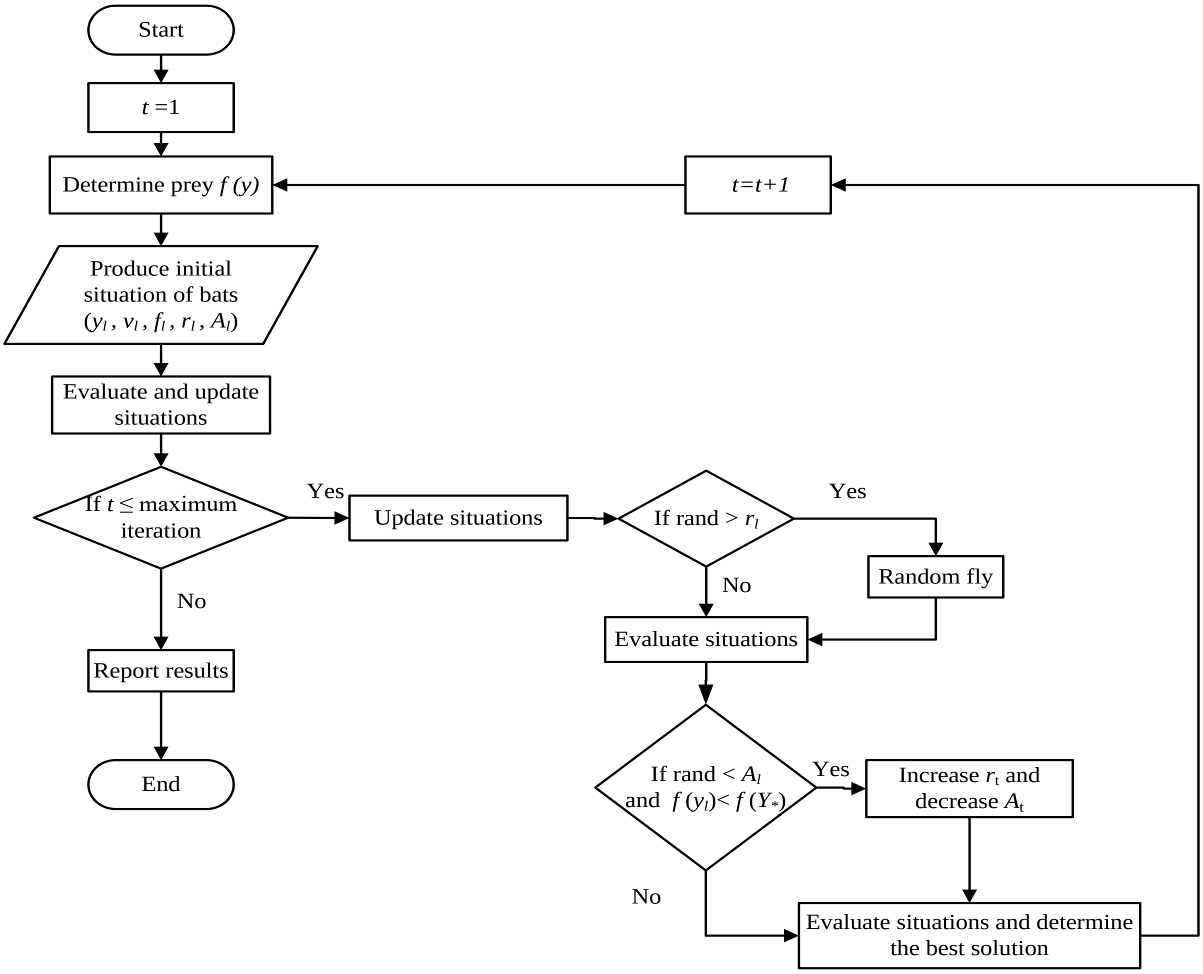

Fig. 6 Basic steps of the BA (Adapted from Bozorg-Haddad et al. [33])

According Bozorg-Haddad et al. [33], after determination of prey (objective function) and producing the initial situation of bats (position (y_l), velocity (v_l), frequency (f_l), pulsation (r_l), loudness (A_l)), the objective function is used to evaluate and update situations (refers Fig.5). There are certain rules to follow in order to update the lth bat's position (y_l) and velocity (v_l) in a d-dimensional search space (update situations). The outcomes will be a new position [y_l (t)] and velocities [v_l (t)] at time step (t) and frequency (f_l). In implementations, the positions of the bats are obtained from the solution of the optimization problem. For the local search part (random fly), once a solution has been selected among the current best solutions, a new solution for each bat is generated locally using random walk (y(t)) [33].

The advantage of the BA in comparison with the optimization methods such as dynamic programming, linear programming and nonlinear programming is their superior performance to find global optimal solutions of the optimisation problems in various fields of water resources engineering, complex engineering problem, and, in particular, in the optimization of reservoir system operation [33]. BA is simple, flexible and easy to implement and better than other algorithms in terms of accuracy and efficiency [33] in solving energy generation problems [33, 34]. It can solve a wide range of problems and highly nonlinear problems including complicated problem [35]. BA provides the best solution in a short time and promising optimal solutions [35]. Therefore, it has been considered as a powerful method for solving engineering optimization tasks [32]. On the other hand, the disadvantages of BA have been identified that there is no mathematical analysis to link the parameters with convergence rates, and BA converge very quickly at the early stage and then convergence rate slows down. Accuracy of BA may be limited if the number of function evaluations is not high and BA also is not well-defined on the best values for most of the applications [35].

III. DISCUSSIONS

Hydropower is one of the technologies in renewable energy. It is harnessed water to produce electricity or power machinery. Hydropower uses water that is not reduced or lessen in the process since the water cycle is an endless and constant recharging system. Hence, for the effectiveness of hydropower plant management and scheduling, there is a necessity to identify a suitable method for forecasting future monthly water inflows and electricity production in operational hydrology [36]. Due to limitations of TOPKAPI model and ABC Algorithm, this study preferred to employ ANN and BA Algorithm to forecast the water used and electricity produced at hydropower plants in the study area. Therefore, the study proposed the application of hybrid Bat Algorithm - Artificial Neural Network model to improve the hydrology forecasting for water used and electricity production.

Historical data on water usage and electricity production has been used as input data to forecast for 5 years. It is found that, the hybrid ANN-based model performs better forecasting as compared to the regular ANN model. This hybrid algorithm is better than the conventional ANN as is proven in research done by Hussin et al. [37], Onwuka et al. [38] and Bangyal et al. [39]. A hybrid algorithm is an algorithm that combines two or more other algorithms that solve the same problem, either using one, or switching between them over the sequences of the algorithm. Normally the desired features are combined, so that the overall algorithm performed better than the individual algorithm. A hybrid of metaheuristic Bat Algorithm (BA) with Artificial Neural Network (ANN) technique, a bio-inspired algorithm is proposed to forecast future water used to generate electricity and electricity production at hydropower plants. The Hybrid Bat Algorithm-Artificial Neural Network (BA-ANN) was designed and written clearly to customize the series time series input data and assumptions [37].

In brief, hybrid BA-ANN started with the BA to select the objective function. The objective function was used to evaluate and update situations. Then the weight matrix is initialized with the initial population or situation of bats that are: position (y_l), velocity (v_l), frequency (f_l), pulsation (r_l), and loudness (A_l). Followed by ANN to start the training phase, whereby, the input data is fed into ANN's architecture with multiple layers. The outputs are computed using random bias and weights until the weights are initialized and changed. The process will repeat until the error of predicted data is less than the decided fitness function. In the next step, BA specifies the best solution by means of the results obtained from the neural network. An ANN-based predictive model is used to uncover water used and electricity production trends. In the ANN phases, a clustering ANN is first developed to identify those days with similar hourly load patterns and natural inflows. Meanwhile, the BA is used to conclude the best result from the application of ANN. Further study will be conducted for more details of this hybrid BA-ANN algorithm.

IV. CONCLUSIONS

Forecasting of energy production for power plants is an essential tool for ensuring continuity of power supply for user demand, reserve power supply and transaction between power plants. The BA-ANN represents a promising modeling method, particularly for sets of non-linear data which are commonly collected in hydrology production. Previous studies such as Onwuka et al. (2018), Hussin et al. (2016), Wang et al. (2009) and many others studies have found that the hybrid BA-ANN to be very efficient and there agreed that it is a promising and powerful tool in forecasting. The use of ANN for the prediction and forecasting of water resource variables are well-established in the research area. The accuracy of ANN-based forecast model is found to be dependent on a number of parameters such as input combination, forecast model architecture, activation functions and training algorithm, and other external variables affecting inputs of the forecast model. The combination of ANN with a metaheuristic algorithm and structure BA can provide a powerful tool for forecasting a time series. A forecasting method based on ANN trained with a BA in order to predict the next day's production. As stated, ANN has the ability to solve problems with nonlinear variables. The ability of ANN along with the powerful search and fast convergence of the BA was used to detect optimum solutions. In the long-term, the BA-ANN model is useful in water resources applications such as hydropower generation, environment protection, drought management, operation of water supply utilities, optimal reservoir operation, and sustainable development of water resources.

REFERENCES

1. World Energy Markets Observatory (WEMO) 2017 report.
2. Global Energy Statistical Yearbook 2018. https://yearbook.enerdata.net/electricity/electricity-domestic-consumption-data.html. [Accessed 20 March 2019].
3. World Energy Resources report, 24th edition. World Energy Council 2016. United Kingdom
4. Hydropower Status Report 2018. Sector Trends and Insights. International Hydropower Association.
5. Paish, Oliver. "Small hydro power: technology and current status." (Renewable and sustainable energy reviews 6, no. 6, 2002): 537-556.
6. Askari Mohammad Bagher, Mirzaei Vahid, Mirhabibi Mohsen, Dehghani Parvin. Hydroelectric Energy Advantages and Disadvantages. (American Journal of Energy Science. Vol. 2, No. 2, 2015). pp. 17-20.
7. Machman-Hunt, N. "Small Hydropower Systems: Energy Efficiency and Renewable Energy Clearinghouse (EREC) Fact Sheet." US Department of Energy, National Renewable Energy Laboratory. (2001).
8. Mayor, Beatriz, Ignacio Rodríguez-Muñoz, Fermín Villarroya, Esperanza Montero, and Elena López-Gunn. "The role of large and small scale hydropower for energy and water security in the Spanish Duero Basin." (Sustainability 9, no. 10. 2017): pp.1807
9. http://www.progea.net/prodotti.php?p=TOPKAPI&lin=inglese. [Accessed 20 March 2019]
10. Ciarapica, L., and E. Todini. "TOPKAPI: A model for the representation of the rainfall-runoff process at different scales." (Hydrological Processes 16, no. 2, 2002): pp. 207-229.
11. Coccia, Gabriele, C. Mazzetti, E. A. Ortiz, and E. Todini. "Application of the TOPKAPI model within the DMIP 2 project." (In 23rd Conference on Hydrology.) 2009. pp.1 -19
12. Plate, Erich J. "Early warning and flood forecasting for large rivers with the lower Mekong as example." (Journal of Hydro-environment Research 1, No. 2, 2007): pp.80-94.
13. Konz, M., M. Chiari, Stefan Rimkus, J. M. Turowski, Peter Molnar, D. Rickenmann, and Paolo Burlando. "Sediment transport modelling in a distributed physically based hydrological catchment model." (Hydrology and Earth System Sciences 15, no. 9, 2011): 2821-2837.
14. Cleophas Mulongo. "Is Artificial Intelligence a Part of Computer Science?" https://www.technotification.com/ 2018/10/is-ai-part-of-computer-science.html. 2018 [Accessed 2 April 2019].
15. Raza, Farah Naaz. "Artificial intelligence techniques in software engineering (AITSE)." (In International MultiConference of Engineers and Computer Scientists IMECS 2009, vol. 1. 2009)
16. Hayati, Mohsen, and Yazdan Shirvany. "Artificial neural network approach for short term load forecasting for Illam region." (World Academy of Science, Engineering and Technology 28, 2007): pp. 280-284.
17. Maind, Sonali B., and Priyanka Wankar. "Research paper on basic of artificial neural network." (International Journal on Recent and Innovation Trends in Computing and Communication 2, no. 1, 2014): pp. 96-100.
18. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology."Artificial neural networks in hydrology. I: Preliminary concepts." (Journal of Hydrologic Engineering 5, no.2, 2000): pp.115-123.
19. Agatonovic-Kustrin, S., and R. Beresford. "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research." (Journal of pharmaceutical and biomedical analysis 22, no.5, 2000): pp.717-727.
20. Özşahin, Şükrü. "The use of an artificial neural network for modeling the moisture absorption and thickness swelling of oriented strand board." (BioResources 7, no. 1, 2012): 1053-1067.
21. He, Zhibin, Xiaohu Wen, Hu Liu, and Jun Du. "A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region." (Journal of Hydrology 509, 2014): pp. 379-386.
22. Engelbrecht, Andries P. *Computational intelligence: an introduction*. (John Wiley & Sons, 2007).
23. Sauhats, Antans, Roman Petrichenko, Zane Broka, Karlis Baltputnis, and Dmitrijs Sobolevskis. "ANN-based forecasting of hydropower reservoir inflow." (In 2016 57th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), 2016). pp. 1-6. IEEE
24. Amber, K. P., R. Ahmad, M. W. Aslam, A. Kousar, M. Usman, and M. S. Khan. "Intelligent techniques for forecasting electricity consumption of buildings." (Energy 157, 2018): pp. 886-893.
25. Cobaner, Murat, Tefaruk Haktanir, and Ozgur Kisi. "Prediction of Hydropower Energy Using ANN for the Feasibility of Hydropower Plant Installation to an Existing Irrigation Dam." (Water Resource Management 22, 2008): pp 757 - 774.
26. Karaboga, Dervis, and Bahriye Basturk. "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm." Journal of global optimization 39, no. 3 (2007): 459-471.
27. Bansala, Jagdish Chand, Anshul Gopala, and Atulya K. Naga. "Stability analysis of Artificial Bee Colony optimization algorithm." (Swarm and Evolutionary Computation 41, 2018): pp 9-19.
28. Chena, Xu, Huaglory Tianfield, and Kangji Li. "Self-adaptive differential artificial bee colony algorithm for globaloptimization problems." (Swarm and Evolutionary Computation 45, 2019): pp. 70-91.
29. Bolaji, Asaju La'aro, Ahamad Tajudin Khader, Mohammed Azmi Al-Betar, and Mohammed A. Awadallah. "Artificial bee colony algorithm, its variants and applications: A survey." (Journal of Theoretical & Applied Information Technology 47, no. 2, 2013).
30. Yang, Jingyuan, Qiaoyong Jianga, Lei Wang, Shuai Liu, Yu-Dong Zhang, Wei Li, and Bin Wang. "Anadaptive encoding learning for artificial bee colony algorithms." (Journal of Computational Science 30, 2019): pp 11-27.
31. Dokeroglu, Tansel, Ender Sevin, and Ahmet Cosar. "Artificial bee colony optimization for the quadratic assignment problem." (Applied Soft Computing Journal 76, 2019): pp 595-606.
32. Balamurugan, R., A. M. Natarajan, and K. Premalatha. "Stellar-mass black hole optimization for biclustering microarray gene expression data." (Applied Artificial Intelligence 29, no. 4, 2015): pp. 353-381.
33. Bozorg-Haddad, Omid, Iman Karimirad, Samaneh Seifollahi-Aghmiuni, and Hugo A. Loáiciga. "Development and application of the bat algorithm for optimizing the operation of reservoir systems." (Journal of Water Resources Planning and Management 141, no. 8, 2014): 04014097.
34. Niknam, Taher, Sajjad Sharifinia, and Rasoul Azizipanah-Abarghooee. "A new enhanced bat-inspired algorithm for finding linear supply function equilibrium of GENCOs in the competitive electricity market." (Energy Conversion and Management 76, 2013): pp. 1015-1028.
35. Ayushi Gagneja Priya Kaushal. Bat Algorithm. (Engineering. 2016). https://www.slideshare.net
36. Wang, Wen-Chuan, Kwok-Wing Chau, Chun-Tian Cheng, and Lin Qiu. "A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series." (Journal of hydrology 374, no. 3-4, 2009): pp. 294-306.
37. Hussin, S. N. H. S., M. A. Malek, N. S. Jaddi, and Z. A. Hamid. 2016. "Hybrid Metaheuristic of Artificial Neural Network - Bat Algorithm in Forecasting Electricity Production and Water Consumption at Sultan Azlan Shah Hydropower Plant." 2016 IEEE International Conference on Power and Energy (PECon).
38. Onwuka, E. N., S. Aliyu, M. Okwori, B. A. Salihu, A. J. Onumanyi, and H. Bello-Salau. "Optimal Design of Colpitts Oscillator Using Bat Algorithm and Artificial Neural Network (BA-ANN)." (In International Conference on Information Systems Architecture and Technology, Springer, Cham, 2018): pp. 29-38.
39. Manikanthan, S.V., Padmapriya, T., "An efficient cluster head selection and routing in mobile WSN" International Journal of Interactive Mobile Technologies, 2019.