WATER LEVEL FORECASTING USING FEED FORWARD NEURAL NETWORKS OPTIMIZED BY AFRICAN BUFFALO ALGORITHM (ABO)

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SUPERVISOR'S DECLARATION

I hereby declare that we have checked this thesis, and, in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Computer Science.

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STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ABSTRAK

Ramalan paras air adalah proses penting dalam pengurusan banjir, penentuan potensi aliran sungai, analisis aliran alam sekitar, pengurusan pertanian dan penjanaan kuasa hidro. Penyelidik telah berusaha sejak dua dekad yang lalu dalam mengeksploitasi evolusi keupayaan komputer bagi membangunkan sistem ramalan paras air yang berfokus pada ketepatan bagi mengurangkan kesan-kesan negatif yang disebabkan oleh perubahan jumlah air di sungai kepada masyarakat sekitar. Kajian mendapati bahawa Rangkaian Neural Buatan (ANN) yang diilhamkan oleh sistem saraf biologi telah berjaya dalam menyelesaikan beberapa masalah dan dianggap sebagai alat ramalan yang berpotensi. Salah satu aspek utama ANN yang memainkan peranan utama dalam kecekapannya adalah proses pembelajaran, telah menjadi tumpuan kebanyakan penyelidik dalam beberapa ketika. Ketika latihan rangkaian saraf, cabaran utama adalah ketidaklinearan dan set terbaik parameter bagi kawalan utama (pemberat dan pemberat sebelah). Walaupun terbukti kejayaan algoritma keturunan-kecerunan seperti ‘Backpropagation’ (BP) untuk latihan ANN, mereka masih mempunyai beberapa kelemahan seperti terperangkap dalam minima tempatan dan penumpuan lambat. Ini menjadikan Algoritma Kepintaran ‘Swarm’ (SI) alternatif yang boleh dipercayai untuk mengurangkan kelemahan ini. Kajian ini mencadangkan algoritma latihan baru berdasarkan algoritma metaheuristik ‘Swarm’ baru-baru ini yang dinamakan algoritma Pengoptimuman Buffalo Afrika (ABO). ABO telah berjaya menyelesaikan banyak masalah dalam pembaikan. Oleh itu, kajian ini menyiasat kecekapannya dalam latihan ‘Multilayer Perceptron Neural Networks’ (MLPNN) dan menyelesaikan masalah BP. Di samping itu, kajian iti menyiasat kesan bilangan neuron dalam lapisan tersembunyi, bilangan populasi kawanan, dan kriteria berhenti (lelaran) pada prestasi model. Set data aras air sungai dipilih bagi menguji algoritma yang dilatih IABO dan hasilnya disahkan dengan penanda aras prestasi algoritma pengoptimuman ‘Partikel Swarm’ (PSO) dan ‘Back-Propagatio’n (BP). Hasil menunjukkan keberkesanan algoritma terlatih IABO dalam menghindari minima tempatan, kelajuan konvergensi dan ketepatan berbanding algoritma penandaarasan (BP dan PSO).

ABSTRACT

Water is an essential requirement for human life and activities associated with industries and agriculture. An accurate forecasting model would be helpful in providing a warning of impending flood during the flooding time and assist in regulating reservoir outflows during the low flows. This reason motivated the researchers to exploit the evolution of machine learning to develop water level forecasting systems that were characterized by accuracy, simplicity and low cost. This development goal is to reduce the impact of water variation in river water levels. The machine learning applications, especially Feed forward neural network (FFNN) which inspired from the human biological nervous system have been successful in solving several complex problems. The FFNN training process which is an optimization task to find the optimal controlling parameters (weights and biases) is considered as the main issues in any model performance. Due to that, many algorithms employ different training algorithms to guide the network for providing an accurate result with less training and testing error. These algorithms have succeeded with different accuracy levels, but it is still suffering from some weaknesses. Weakness such as trapped in local minima, slow convergence and finding a good rate between exploitation and exploration of the search space. This research proposed a swarm intelligence training algorithm, Improved African Buffalo Optimization algorithm (IABO) based on the Metaheuristic method called the African Buffalo Optimization algorithm (ABO). ABO has been successful in solving many improvement problems. These successes motivate the development and investigation of its efficiency in training Feed Forward Neural Networks (FFNNs), for solving training process issues. Additionally, the study investigated the effect of neurons number in the hidden layer, the number of population swarm, and the stopping criteria (iterations) on the model's performance. Water level data set was chosen to test the proposed IABO-trained algorithm. The results were verified by benchmarking with the performance of the Particle Swarm Optimization (PSO) and Backpropagation (BP) algorithms. The results demonstrated the superiority of the IABO-trained algorithm in avoiding local minima, convergence speed, and accuracy compared to the benchmarking (BP and PSO) algorithms in water level forecasting tasks.

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LIST OF SYMBOLS

$\boldsymbol{w}$	Connection weight (MLP)
$\boldsymbol{Ii}$	Input of neuron i
$\boldsymbol{b}$	Bias
$\boldsymbol{E}$	Error vector
$\boldsymbol{Si}$	Output of neuron i
μ	Momentum (BP)
ε	learning rate(BP)
$\boldsymbol{h}$	Hidden neuron (MLP)
$\boldsymbol{o}$	Output neuron (MLP)
$\boldsymbol{v^k}$	Current Velocity (PSO)
$\boldsymbol{v^{k+1}}$	New Velocity (PSO)
$\boldsymbol{s^k}$	Current Position (PSO)
$\boldsymbol{s^{k+1}}$	New position (PSO)
$\boldsymbol{C1}$	acceleration constants for $gbest$ (PSO)
$\boldsymbol{C2}$	acceleration constants for $pbest$ (PSO)
$\boldsymbol{r1}$	Random number (PSO)
$\boldsymbol{r2}$	Random number (PSO)
$\boldsymbol{w_p}$	inertia weight (PSO)
$\boldsymbol{lb}$	Local best swarm position (PSO)
$\boldsymbol{gb}$	Global best swarm position (PSO)
$\boldsymbol{m^k}$	Current exploitation (ABO)
$\boldsymbol{m^{k+1}}$	New exploitation (ABO)
$\boldsymbol{w^k}$	Current exploration (ABO)
$\boldsymbol{w^{k+1}}$	New exploration (ABO)
$\boldsymbol{lp1}$	learning factors (ABO)
$\boldsymbol{lp2}$	learning factors (ABO)
$\boldsymbol{\lambda}$	Random number (ABO)
$\boldsymbol{bp}$	Local best swarm position (ABO)
$\boldsymbol{gb}$	Global best swarm position (ABO)
$\boldsymbol{MSE}$	Mean Square Error
$\boldsymbol{MAE}$	Mean Absolute Error
$\boldsymbol{RMSE}$	Root Mean Square Error
$\boldsymbol{R}$	Regression

LIST OF ABBREVIATIONS

CRED	Centre for Research on the Epidemiology of Disasters
ANN	Artificial Neural Network
MLPNN	Multilayer Perceptron Neural Networks
FFNN	Feed Forward Neural Networks
GD	Gradient Descent
BP	Backpropagation
GA	Genetic Algorithm
ABC	Artificial Bee Colony
PSO	Particle Swarm Optimization
FF	Fireflies
NFL	No-Free-Lunch theorem
ABO	African Buffalo Optimization
IABO	Improve African Buffalo Optimization
SI	Swarm Intelligence
AI	Artificial Intelligence
ML	Machine Learning
RBF	Radial Basis Function
SOM	Self-Organizing Map
DE	Differential Evaluation
SVM	Support Vector Machine
NF	Neuro-Fuzzy
ANFIS	Adaptive-Network-based Fuzzy Inference System
SC	Steepness Coefficient
FSP	Flood water Storage Pond
GT	Gamma Test
ARMAX	Autoregressive Moving Average with Exogenous
CE	Coefficient of Efficiency
WT	Wavelet Transform
GWO	Grey Wolf Optimizer
CS	Cuckoo Search
GSA	Gravitational Search Algorithm

REFERENCES

Afan, H. A., El-Shafie, A., Yaseen, Z. M., Hameed, M. M., Mohtar, W. H. M. W., and Hussain, A. (2015). ANN based sediment prediction model utilizing different input scenarios. *Water Resources Management,* 29(4), pp.1231-1245.

Agatonovic-Kustrin, S., and Beresford, R. (2000). Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *Journal Of Pharmaceutical And Biomedical Analysis,* 22(5), pp.717-727.

Ahmed, J. A., and Sarma, A. K. (2007). Artificial neural network model for synthetic streamflow generation. *Water Resources Management,* 21(6), pp.1015-1029.

Al-Hadi, I. A. A., Hashim, S. Z. M., and Shamsuddin, S. M. H. (2011). Bacterial Foraging Optimization Algorithm for neural network learning enhancement. *Proceedings of 11th International Conference on Hybrid Intelligent Systems*, pp.200-205.

Aljarah, I., Faris, H., and Mirjalili, S. (2018). Optimizing connection weights in neural networks using the whale optimization algorithm. *Soft Computing,* 22(1), pp.1-15.

Alpsan, D., Towsey, M., Ozdamar, O., Tsoi, A. C., and Ghista, D. N. (1995). Efficacy of modified backpropagation and optimisation methods on a real-world medical problem. *Neural Networks,* 8(6), pp.945-962.

Alvisi, S., and Franchini, M. (2011). Fuzzy neural networks for water level and discharge forecasting with uncertainty. *Environmental Modelling & Software,* 26(4), pp.523-537.

Araújo, R. d. A. (2011). A class of hybrid morphological perceptrons with application in time series forecasting. *Knowledge-Based Systems,* 24(4), pp.513-529.

Awchi, T. A. (2014). River discharges forecasting in northern Iraq using different ANN techniques. *Water Resources Management,* 28(3), pp.801-814.

Azrag, M., Kadir, T. A., Odili, J., and Essam, M. (2017). A Global African Buffalo Optimization. *International Journal of Software Engineering & Computer Sciences,* 3, pp.138-145.

Bates, B. C., and Townley, L. R. (1988). Nonlinear, discrete flood event models, 3. Analysis of prediction uncertainty. *Journal of Hydrology,* 99(1-2), pp.91-101.

Bazartseren, B., Hildebrandt, G., and Holz, K.-P. (2003). Short-term water level prediction using neural networks and neuro-fuzzy approach. *Neurocomputing,* 55(3-4), pp.439-450.

Beheshti, S., Hashemi, M., Sejdic, E., and Chau, T. (2011). Mean Square Error Estimation in Thresholding. *IEEE Signal Processing Letters,* 18(2), pp.103-106.

Berneti, S. M., and Shahbazian, M. (2011). An imperialist competitive algorithm artificial neural network method to predict oil flow rate of the wells. *International Journal Of Computer Applications,* 26(10), pp.47-50.

Bhattacharya, B., and Solomatine, D. P. (2006). Machine learning in sedimentation modelling. *Neural Networks,* 19(2), pp.208-214.

Biabangard-Oskouyi, A., Atashpaz-Gargari, E., Soltani, N., and Lucas, C. (2009). Application of imperialist competitive algorithm for materials property characterization from sharp indentation test. *International Journal of Engineering Simulation,* 10(1), pp.11-12.

Blum, C., and Socha, K. (2005). Training feed-forward neural networks with ant colony optimization: An application to pattern classification. *Proceedings of 5th International Conference on Hybrid Intelligent Systems*, 6.

Brajevic, I., and Tuba, M. (2013). Training feed-forward neural networks using firefly algorithm. Proceedings of the 12th International Conference on Artificial Intelligence, Knowledge Engineering and Data Bases, pp.156-161.

Brameier, M. (2009). Neural Networks in Data-Mining and Knowledge Discovery, *Encyclopedia of Complexity and Systems Science*, pp.1812-1826.

Campolo, M., Andreussi, P., and Soldati, A. (1999). River flood forecasting with a neural network model. *Water Resources Research,* 35(4), pp.1191-1197.

Carvalho, M., and Ludermir, T. B. (2006). Particle swarm optimization of feed-forward neural networks with weight decay. *Proceedings of 6th International Conference on Hybrid Intelligent Systems*, pp.5-5.

Chan, F. T., and Tiwari, M. K. (2007). Preface: swarm intelligence, focus on ant and particle swarm optimization. *Swarm Intelligence, Focus on Ant and Particle Swarm Optimization*, InTech.

Chan, N. W. (2012). Managing urban rivers and water quality in Malaysia for sustainable water resources. *International Journal of Water Resources Development,* 28(2), pp.343-354.

Chandra, P., and Singh, Y. (2004). An activation function adapting training algorithm for sigmoidal feedforward networks. *Neurocomputing,* 61, pp.429-437.

Chandwani, V., Agrawal, V., and Nagar, R. (2015). Modeling slump of ready mix concrete using genetic algorithms assisted training of Artificial Neural Networks. *Expert Systems with Applications*, 42(2), pp.885-893.

Chang, F.-J., and Chang, Y.-T. (2006). Adaptive neuro-fuzzy inference system for prediction of water level in reservoir. *Advances in Water Resources,* 29(1), pp.1-10.

Chang, F.J., Chen, P.A., Lu, Y.-R., Huang, E., and Chang, K.Y. (2014). Real-time multi-step-ahead water level forecasting by recurrent neural networks for urban flood control. *Journal of Hydrology,* 517, pp.836-846.

Chatterjee, S., Sarkar, S., Hore, S., Dey, N., Ashour, A. S., and Balas, V. E. (2017). Particle swarm optimization trained neural network for structural failure prediction of multistoried RC buildings. *Neural Computing and Applications*, 28(8), pp.2005-2016.

Chauhan, N. C., Kartikeyan, M. V., and Mittal, A. (2012). Soft Computing Methods for Microwave and Millimeter-Wave Design Problems, 392.

Cigizoglu, H. K., and Alp, M. (2006). Generalized regression neural network in modelling river sediment yield. *Advances in Engineering Software*, 37(2), pp.63-68.

Civicioglu, P. (2013). Backtracking search optimization algorithm for numerical optimization problems. *Applied Mathematics and Computation,*219(15), pp.8121-8144.

Costabile, P., Costanzo, C., Macchione, F., and Mercogliano, P. (2012). Two-dimensional model for overland flow simulations: a case study. *Eur Water,* 38, pp.13-23.

Das, J., and Acharya, B. (2003). Hydrology and assessment of lotic water quality in Cuttack city, India. *Water, Air, and Soil Pollution,* 150(1-4), pp.163-175.

DasGupta, B., and Schnitger, G. (1993). The power of approximating: a comparison of activation functions. *Advances in Neural Information Processing Systems*, pp.615-622.

Derrac, J., García, S., Molina, D., and Herrera, F. (2011). A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. *Swarm and Evolutionary Computation,* 1(1), pp.3-18.

Dlamini, N. S., Kamal, M. R., Soom, M. A. B. M., Mohd, M. S. F. b., Abdullah, A. F. B., and Hin, L. S. (2017). Modeling potential impacts of climate change on streamflow using projections of the 5th assessment report for the Bernam River Basin, Malaysia. *Water,* 9(3), 226.

Dreiseitl, S., and Ohno-Machado, L. (2002). Logistic regression and artificial neural network classification models: a methodology review. *Journal of Biomedical Informatics,* 35(5-6), pp.352-359.

Duch, W., and Jankowski, N. (1999). Survey of neural transfer functions. *Neural Computing Surveys,* 2(1), pp.163-212.

Dundar, G., and Rose, K. (1995). The effects of quantization on multilayer neural networks. *IEEE Transactions on Neural Networks,* 6(6), 1446-1451.

Eberhart, R., and Kennedy, J. (1995). A new optimizer using particle swarm theory. *Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, pp.39-43.

Elfithri, R., and Mokhtar, M. B. (2018). Integrated Water Resources Management in Malaysia: Some Initiatives at the Basin Level, *Water Resources Management* , pp. 231-244.

Elman, J. L. (1990). Finding structure in time. *Cognitive Science*, 14(2), pp.179-211.

Eskandar, H., Sadollah, A., Bahreininejad, A., and Hamdi, M. (2012). Water cycle algorithm–A novel metaheuristic optimization method for solving constrained engineering optimization problems. *Computers & Structures,* 110, pp.151-166.

Evers, G. I., and Ghalia, M. B. (2009). Regrouping particle swarm optimization: A new global optimization algorithm with improved performance consistency across benchmarks. *Proceedings of IEEE International Conference on Systems, Man and Cybernetics*, pp.3901-3908.

Faris, H., Aljarah, I., and Mirjalili, S. (2018). Improved monarch butterfly optimization for unconstrained global search and neural network training. *Applied Intelligence,* 48(2), pp.445-464.

Ghaffari, A., Abdollahi, H., Khoshayand, M., Bozchalooi, I. S., Dadgar, A., and Rafiee-Tehrani, M. (2006). Performance comparison of neural network training algorithms in modeling of bimodal drug delivery. *International Journal Of Pharmaceutics,* 327(1-2), pp.126-138.

Ghazali, R., Hussain, A. J., Al-Jumeily, D., and Merabti, M. (2007). Dynamic ridge polynomial neural networks in exchange rates time series forecasting. *International Conference on Adaptive and Natural Computing Algorithms*, pp.123-132.

Ghorbani, M. A., Khatibi, R., Goel, A., FazeliFard, M. H., and Azani, A. (2016). Modeling river discharge time series using support vector machine and artificial neural networks. *Environmental Earth Sciences,* 75(8), 685.

Giuliani, M., Pianosi, F., and Castelletti, A. (2015). Making the most of data: an information selection and assessment framework to improve water systems operations. *Water Resources Research,* 51(11), pp.9073-9093.

Gordan, B., Armaghani, D. J., Hajihassani, M., and Monjezi, M. (2016). Prediction of seismic slope stability through combination of particle swarm optimization and neural network. *Engineering with Computers,* 32(1), pp.85-97.

Gudise, V. G., and Venayagamoorthy, G. K. (2003). Comparison of particle swarm optimization and backpropagation as training algorithms for neural networks *Proceedings of the IEEE Swarm Intelligence Symposium*, pp.110-117.

Hamill, T. M. (1999). Hypothesis tests for evaluating numerical precipitation forecasts. *Weather and Forecasting*, 14(2), pp.155-167.

Han, D., Chan, L., and Zhu, N. (2007). Flood forecasting using support vector machines. *Journal of Hydroinformatics,* 9(4), pp.267-276.

Ho, S., Xie, M., and Goh, T. (2002). A comparative study of neural network and Box-Jenkins ARIMA modeling in time series prediction. *Computers & Industrial Engineering,* 42(2-4), pp.371-375.

Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks,* 2(5), pp.359-366.

Huang, G.-B., and Chen, L. (2007). Convex incremental extreme learning machine. *Neurocomputing,* 70(16-18), pp.3056-3062.

Huang, W.-b., Zhao, D., Sun, F., Liu, H., and Chang, E. Y. (2015). Scalable Gaussian Process Regression Using Deep Neural Networks. *Proceedings of the 24th International Joint Conference on Artificial Intelligence*, pp.3576-3582.

Jin, W., Li, Z. J., Wei, L. S., and Zhen, H. (2000). The improvements of BP neural network learning algorithm. *Proceedings of 5th International Conference on Signal Processing*, 3, pp.1647-1649.

Johnson, D. S., Aragon, C. R., McGeoch, L. A., and Schevon, C. (1991). Optimization by simulated annealing: an experimental evaluation; part II, graph coloring and number partitioning. *Operations Research,* 39(3), pp.378-406.

Jordan, M. I., and Rumelhart, D. E. (1992). Forward models: Supervised learning with a distal teacher. *Cognitive Science,* 16(3), pp.307-354.

Karaboga, D., Akay, B., and Ozturk, C. (2007). Artificial bee colony (ABC) optimization algorithm for training feed-forward neural networks. *Proceedings of International Conference on Modeling Decisions for Artificial Intelligence*, pp.318-329.

Karaboga, D., and Ozturk, C. (2009). Neural networks training by artificial bee colony algorithm on pattern classification. *Neural Network World,* 19(3), 279.

Karri, R. R., and Sahu, J. (2018). Modeling and optimization by particle swarm embedded neural network for adsorption of zinc (II) by palm kernel shell based activated carbon from aqueous environment. *Journal of Environmental Management,* 206178-191.

Kaur, K., Salgotra, R., and Singh, U. (2017). An improved firefly algorithm for numerical optimization. *Proceedings of International Conference on Innovations in Information, Embedded and Communication Systems*, pp.1-5.

Khare, K., Darekar, O., Gupta, P., and Attar, V. (2017). Short term stock price prediction using deep learning. *Proceedings of 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology*, 482-486.

Knight, K. (1990). Connectionist ideas and algorithms. *Communications of the ACM,* 33(11), pp.58-74.

Kourentzes, N., Barrow, D. K., and Crone, S. F. (2014). Neural network ensemble operators for time series forecasting. *Expert Systems with Applications,* 41(9), pp.4235-4244.

Kowalski, P. A., and Łukasik, S. (2016). Training neural networks with krill herd algorithm. *Neural Processing Letters*, 44(1), pp.5-17.

Kuo, R., and Cohen, P. (1998). Intelligent tool wear estimation system through artificial neural networks and fuzzy modeling. *Artificial Intelligence in Engineering,* 12(3), pp.229-242.

Kuok, K. K., Harun, S., and Shamsuddin, S. (2010). Particle swarm optimization feedforward neural network for modeling runoff. *International Journal of Environmental Science & Technology,* 7(1), pp.67-78.

Lehmen, V. (1988). Factors influencing learning by backpropagation. *Proceedings of IEEE International Conference onNeural Networks*, pp.335-341.

Leong, K. H., Tan, L. B., and Mustafa, A. M. (2007). Contamination levels of selected organochlorine and organophosphate pesticides in the Selangor River, Malaysia between 2002 and 2003. *Chemosphere,* 66(6), pp.1153-1159.

Lian, C., Zeng, Z., Yao, W., and Tang, H. (2012). Displacement prediction model of landslide based on ensemble of extreme learning machine. *Proceedings of International Conference on Neural Information Processing*, pp.240-247.

Liong, S.Y., Lim, W.H., and Paudyal, G. N. (2000). River stage forecasting in Bangladesh: neural network approach. *Journal of Computing in Civil Engineering,* 14(1), pp.1-8.

Liong, S. Y., and Sivapragasam, C. (2002). Flood stage forecasting with support vector machines. *JAWRA Journal of the American Water Resources Association,* 38(1), pp.173-186.

Liu, F., Xu, F., and Yang, S. (2017). A flood forecasting model based on deep learning algorithm via integrating stacked autoencoders with BP neural network. *Proceedings of IEEE 3rd International Conference on Multimedia Big Data*, pp.58-61.

Liu, H., Tian, H.-q., Chen, C., and Li, Y.-f. (2013). An experimental investigation of two Wavelet-MLP hybrid frameworks for wind speed prediction using GA and PSO optimization. *International Journal of Electrical Power & Energy Systems*, 52, pp.161-173.

Loucks, D. P., and Van Beek, E. (2017). Water Resource Systems Planning and Management: An Introduction to Methods, Models, and Applications. Springer.

Luger, G. F. (2005). Artificial Intelligence: Structures and Strategies for Complex Problem Solving. Pearson education.

McCulloch, W. S., and Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The Bulletin Of Mathematical Biophysics,* 5(4), pp.115-133.

Mendes, R., Cortez, P., Rocha, M., and Neves, J. (2002). Particle swarms for feedforward neural network training. *Proceedings of the International Joint Conference on Neural Networks*, *2,* pp.1895-1899.

Mirjalili, S. (2015). How effective is the Grey Wolf optimizer in training multi-layer perceptrons. *Applied Intelligence,* 43(1), pp.150-161.

Mirjalili, S., Hashim, S. Z. M., and Sardroudi, H. M. (2012). Training feed forward neural networks using hybrid particle swarm optimization and gravitational search algorithm. *Applied Mathematics And Computation,* 218(22), pp.11125-11137.

Montana, D. J., and Davis, L. (1989). Training feedforward neural networks using genetic algorithms. *Proceedings of the International Joint Conference on Artificial Intelligence*, *89,* pp.762-767.

Moody, J., and Utans, J. (1992). Principled architecture selection for neural networks: Application to corporate bond rating prediction. *Advances in Neural Information Processing Systems*, pp.683-690.

Moslemipour, G., Lee, T. S., and Rilling, D. (2012). A review of intelligent approaches for designing dynamic and robust layouts in flexible manufacturing systems. *The International Journal of Advanced Manufacturing Technology*, 60(1-4), pp.11-27.

Mukhopadhyay, M. (2014). A brief survey on bio inspired optimization algorithms for molecular docking. *International Journal of Advances in Engineering & Technology,* 7(3), 868.

Murugadoss, R., and Ramakrishnan, M. (2014). Universal approximation of nonlinear system predictions in sigmoid activation functions using artificial neural networks. *Proceedings of IEEE International Conference on Computational Intelligence and Computing Research*, pp.1-6.

Mwale, F., Adeloye, A., and Rustum, R. (2014). Application of self-organising maps and multi-layer perceptron-artificial neural networks for streamflow and water level forecasting in data-poor catchments: the case of the Lower Shire floodplain, Malawi. *Hydrology Research,* 45(6), pp.838-854.

Najafzadeh, M., Barani, G.-A., and Kermani, M. R. H. (2013). GMDH based back propagation algorithm to predict abutment scour in cohesive soils. *Ocean Engineering,* 59100-106.

Nawi, N. M., Ransing, R. S., Salleh, M. N. M., Ghazali, R., and Hamid, N. A. (2010). An improved back propagation neural network algorithm on classification problems , *Database Theory and Application, Bio-Science and Bio-Technology*, pp. 177-188.

Nguyen, T.T., Huu, Q. N., and Li, M. J. (2015). Forecasting time series water levels on Mekong river using machine learning models. *Proceedings of 7th International Conference on Knowledge and Systems Engineering*, pp.292-297.

Nikoo, M., Ramezani, F., Hadzima-Nyarko, M., Nyarko, E. K., and Nikoo, M. (2016). Flood-routing modeling with neural network optimized by social-based algorithm. *Natural Hazards,* 82(1), pp.1-24.

Nourani, V., Khanghah, T. R., and Baghanam, H. (2014). Implication of feature extraction methods to improve performance of hybrid Wavelet-ANN rainfall–runoff model. *Case Studies In Intelligent Computing*, *pp.*457-498.

Odili, J., Kahar, M. N. M., Anwar, S., and Ali, M. (2017). Tutorials on african buffalo optimization for solving the travelling salesman problem. *International Journal of Software Engineering and Computer Systems*, 3(1), pp.120-128.

Odili, J. B., and Kahar, M. N. M. (2016). African buffalo optimization approach to the design of PID controller in automatic voltage regulator system. *Proceedings of National conference for postgraduate research*, pp.24-25.

Odili, J. B., Kahar, M. N. M., and Anwar, S. (2015). African buffalo optimization: a swarm-intelligence technique. *Procedia Computer Science*, 76, pp.443-448.

Odili, J. B., and Mohmad Kahar, M. N. (2016). Solving the traveling Salesman's problem using the African Buffalo optimization. *Computational Intelligence and Neuroscience,* 20163.

Odili, J. B., and Noraziah, A. (2018). African buffalo optimization for global optimization. *Current Science*, 114(3).

Ojha, V. K., Abraham, A., and Snášel, V. (2017). Metaheuristic design of feedforward neural networks: A review of two decades of research. *Engineering Applications of Artificial Intelligence*, 60, pp.97-116.

Ouyang, H.-T. (2016). Multi-objective optimization of typhoon inundation forecast models with cross-site structures for a water-level gauging network by integrating ARMAX with a genetic algorithm. *Natural Hazards and Earth System Sciences*, 16(8), pp.1897-1909.

Pham, B. T., Bui, D. T., Prakash, I., and Dholakia, M. (2017). Hybrid integration of Multilayer Perceptron Neural Networks and machine learning ensembles for landslide susceptibility assessment at Himalayan area (India) using GIS. *Catena*, 149, pp.52-63.

Pyle, D. (1999). Data preparation for data mining Vol. 1, Morgan Kaufmann.

Qiu, M., Song, Y., and Akagi, F. (2016). Application of artificial neural network for the prediction of stock market returns: The case of the Japanese stock market. *Chaos, Solitons & Fractals,* 85, pp.1-7.

Ramakrishnaiah, C., Sadashivaiah, C., and Ranganna, G. (2009). Assessment of water quality index for the groundwater in Tumkur Taluk, Karnataka State, India. *Journal of Chemistry*, 6(2), pp.523-530.

Raus, M., and Ameling, W. (1994). A Parallel Algorithm for a Dynamic Eta/Alpha Estimation in Backpropagation Learning , *Proceedings of the International Conference on Artificial Neural Networks*, pp. 639-642.

Ren, W., Yang, T., Shi, P., Xu, C.Y., Zhang, K., Zhou, X., Ciais, P. (2018). A probabilistic method for streamflow projection and associated uncertainty analysis in a data sparse alpine region. *Global and Planetary Change,* 165, pp.100-113.

Rezaeianzadeh, M., Tabari, H., Yazdi, A. A., Isik, S., and Kalin, L. (2014). Flood flow forecasting using ANN, ANFIS and regression models. *Neural Computing and Applications*, 25(1), pp.25-37.

Rini, D. P., Shamsuddin, S. M., and Yuhaniz, S. S. (2011). Particle swarm optimization: technique, system and challenges. *International Journal of Computer Applications,* 14(1), pp.19-26.

Romlay, M. R. M., Rashid, M., and Toha, S. (2016). Development of Particle Swarm Optimization Based Rainfall-Runoff Prediction Model for Pahang River, Pekan.

Proceedings of International Conference on Computer and Communication Engineering, pp.306-310.

Rumelhart, D., Hinton, G., and Williams, R. (1986a). Learning internal representations by error propagation. In the PDP Research Group (Eds.), Parallel distributed processing: Explorations in the microstructure of cognition. *Vol. 1: Foundations*, pp. 318-362.

Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1986b). Learning representations by back-propagating errors. *Nature*, 323(6088), pp.533.

Sakai, N., Alsaad, Z., Thuong, N. T., Shiota, K., Yoneda, M., and Mohd, M. A. (2017). Source profiling of arsenic and heavy metals in the Selangor River basin and their maternal and cord blood levels in Selangor State, Malaysia. *Chemosphere.* 184, pp.857-865.

Samarasinghe, S. (2016). Neural Networks for Applied Sciences and Engineering: From Fundamentals to Complex Pattern Recognition. CRC Press.

Santhi, V. A., and Mustafa, A. M. (2013). Assessment of organochlorine pesticides and plasticisers in the Selangor River basin and possible pollution sources. *Environmental Monitoring And Assessment*, 185(2), pp.1541-1554.

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks,* 61, pp.85-117.

Seijas, L. M., Carneiro, R. F., Santana, C. J., Soares, L. S., Bezerra, S. G., and Bastos-Filho, C. J. (2015). Metaheuristics for feature selection in handwritten digit recognition. *Proceedings of Latin America Congress on Computational Intelligence*, pp.1-6.

Seo, Y., Kim, S., Kisi, O., and Singh, V. P. (2015). Daily water level forecasting using wavelet decomposition and artificial intelligence techniques. *Journal of Hydrology,* 520, pp.224-243.

Seyam, M., and Othman, F. (2015). Long-term variation analysis of a tropical river's annual streamflow regime over a 50-year period. *Theoretical and Applied Climatology,* 121(1-2), pp.71-85.

Shah, H., Ghazali, R., and Nawi, N. M. (2011). Using artificial bee colony algorithm for MLP training on earthquake time series data prediction. *Journal of Computing*, 3(6), pp.135-142

Shah, H., and Shah, H. (2014). An Improved Artificial Bee Colony Algorithm for Training Multilayer Perceptron in Time Series Prediction. Universiti Tun Hussein Onn Malaysia.

Simon, D. (2006). Optimal State Estimation: Kalman, H Infinity, and Nonlinear Approaches. John Wiley & Sons.

Soleymani, S. A., Goudarzi, S., Anisi, M. H., Hassan, W. H., Idris, M. Y. I., Shamshirband, S., . . . Ahmedy, I. (2016). A novel method to water level prediction using RBF and FFA. *Water Resources Management,* 30(9), pp.3265-3283.

Solomatine, D. P., and Xue, Y. (2004). M5 model trees and neural networks: application to flood forecasting in the upper reach of the Huai River in China. *Journal of Hydrologic Engineering,* 9(6), pp.491-501.

Sulaiman, M., El-Shafie, A., Karim, O., and Basri, H. (2011). Improved water level forecasting performance by using optimal steepness coefficients in an artificial neural network. *Water Resources Management*, 25(10), pp.2525-2541.

Sun, Z. L., Choi, T. M., Au, K. F., and Yu, Y. (2008). Sales forecasting using extreme learning machine with applications in fashion retailing. *Decision Support Systems*, 46(1), pp.411-419.

Thirumalaiah, K., and Deo, M. (1998). River stage forecasting using artificial neural networks. *Journal of Hydrologic Engineering*, 3(1), pp.26-32.

Tigkas, D., Christelis, V., and Tsakiris, G. (2016). Comparative study of evolutionary algorithms for the automatic calibration of the Medbasin-D conceptual hydrological model. *Environmental Processes*, 3(3), pp.629-644.

Timothy, M. (1993). Practical Neural Network Recipes in C++. Academic Press.

Tsai, J.-T., Chou, J.-H., and Liu, T.-K. (2006). Tuning the structure and parameters of a neural network by using hybrid Taguchi-genetic algorithm. *IEEE Transactions on Neural Networks*, 17(1), pp.69-80.

Ufnalski, B., and Grzesiak, L. (2012). Particle swarm optimization of artificial-neural-network-based on-line trained speed controller for battery electric vehicle. *Bulletin of the Polish Academy of Sciences: Technical Sciences*, 60(3), pp.661-667.

Vaisla, K. S., and Bhatt, A. K. (2010). An analysis of the performance of artificial neural network technique for stock market forecasting. *International Journal on Computer Science and Engineering,* 2(6), pp.2104-2109.

Van den Bergh, F., and Engelbrecht, A. P. (2004). A cooperative approach to particle swarm optimization. *IEEE Transactions On Evolutionary Computation,* 8(3), pp.225-239.

Vanderplaats, G. N. (2007). *Multidiscipline Design Optimization*. Vanderplaats Research & Development, Incorporated.

Vihinen, M. (2012). How to evaluate performance of prediction methods? Measures and their interpretation in variation effect analysis. *BMC Genomics*, *13* (4): S2.

Wang, G., and Guo, L. (2013). A novel hybrid bat algorithm with harmony search for global numerical optimization. *Journal of Applied Mathematics*, 2013(696491), pp.1-21.

Wang, S., Zhang, Y., Dong, Z., Du, S., Ji, G., Yan, J., . . . Phillips, P. (2015). Feed-forward neural network optimized by hybridization of PSO and ABC for abnormal brain detection. *International Journal of Imaging Systems and Technology,* 25(2), pp.153-164.

Wang, X., Tang, Z., Tamura, H., Ishii, M., and Sun, W. (2004). An improved backpropagation algorithm to avoid the local minima problem. *Neurocomputing,* 56, pp.455-460.

Wei, C.-C. (2012). Wavelet kernel support vector machines forecasting techniques: Case study on water-level predictions during typhoons. *Expert Systems with Applications,* 39(5), pp.5189-5199.

Yadav, A., and Sahu, K. (2017). Wind forecasting using artificial neural networks: a survey and taxonomy. *International Journal of Research In Science & Engineering,* 3.

Yang, X., Kumehara, H., and Zhang, W. (2009). Back propagation wavelet neural network based prediction of drill wear from thrust force. *Computer and information Science*, 2(3), 75.

Yaseen, Z. M., El-Shafie, A., Afan, H. A., Hameed, M., Mohtar, W. H. M. W., and Hussain, A. (2016a). RBFNN versus FFNN for daily river flow forecasting at Johor River, Malaysia. *Neural Computing and Applications,* 27(6), pp.1533-1542.

Yaseen, Z. M., El-Shafie, A., Jaafar, O., Afan, H. A., and Sayl, K. N. (2015). Artificial intelligence based models for stream-flow forecasting: 2000–2015. *Journal of Hydrology,* 530, pp.829-844.

Yaseen, Z. M., Kisi, O., and Demir, V. (2016b). Enhancing long-term streamflow forecasting and predicting using periodicity data component: application of artificial intelligence. *Water Resources Management,* 30(12), pp.4125-4151.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, 8(3), pp.338-353.

Zhang, F., Dai, H., and Tang, D. (2014). A conjunction method of wavelet transform-particle swarm optimization-support vector machine for streamflow forecasting. *Journal of Applied Mathematics*, 2014(910196), pp.1-10.

Zhang, G., Patuwo, B. E., and Hu, M. Y. (1998). Forecasting with artificial neural networks:: The state of the art. *International Journal of Forecasting,* 14(1), pp.35-62.

Zhang, J.-R., Zhang, J., Lok, T.-M., and Lyu, M. R. (2007). A hybrid particle swarm optimization–back-propagation algorithm for feedforward neural network training. *Applied Mathematics and Computation,* 185(2), pp.1026-1037.

Zhao, Z., Xu, Q., and Jia, M. (2016). Improved shuffled frog leaping algorithm-based BP neural network and its application in bearing early fault diagnosis. *Neural Computing and Applications,* 27(2), pp.375-385.

Zia, H., Harris, N., Merrett, G., and Rivers, M. (2015). Predicting discharge using a low complexity machine learning model. *Computers and Electronics in Agriculture,* 118, pp.350-360.

Zweiri, Y. H., Whidborne, J. F., Althoefer, K., and Seneviratne, L. D. (2002). A new three-term backpropagation algorithm with convergence analysis. *Proceedings of IEEE International Conference on Robotics and Automation*, *4,* pp.3882-3887.