COMPONENT-WISE ANALYSIS OF METAHEURISTIC ALGORITHMS FOR NOVEL FUZZY-META CLASSIFIER

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ABSTRACT

Metaheuristic research has proposed promising results in science, business, and engineering problems. But, mostly high-level analysis is performed on metaheuristic performances. This leaves several critical questions unanswered due to black-box issue that does not reveal why certain metaheuristic algorithms performed better on some problems and not on others. To address the significant gap between theory and practice in metaheuristic research, this study proposed in-depth analysis approach using component-view of metaheuristic algorithms and diversity measurement for determining exploration and exploitation abilities. This research selected three commonly used swarm-based metaheuristic algorithms – Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Cuckoo Search (CS) – to perform component-wise analysis. As a result, the study able to address premature convergence problem in PSO, poor exploitation in ABC, and imbalanced exploration and exploitation issue in CS. The proposed improved PSO (iPSO), improved ABC (iABC), and improved CS (iCS) outperformed standard algorithms and variants from existing literature, as well as, Grey Wolf Optimization (GWO) and Animal Migration Optimization (AMO) on ten numerical optimization problems with varying modalities. The proposed iPSO, iABC, and iCS were then employed on proposed novel Fuzzy-Meta Classifier (FMC) which offered highly reduced model complexity and high accuracy as compared to Adaptive Neuro-Fuzzy Inference System (ANFIS). The proposed three-layer FMC produced efficient rules that generated nearly 100% accuracies on ten different classification datasets, with significantly reduced number of trainable parameters and number of nodes in the network architecture, as compared to ANFIS.

ABSTRAK

Penyelidikan metaheuristik yang terkini telah memberikan hasil kajian yang lebih baik dalam sains, perniagaan, dan masalah kejuruteraan. Namum, banyak analisis tahap tinggi telah dilakukan atas kebolehupayaan kaedah metaheuristik. Persoalan kritikal yang belum diselesaikan adalah masalah 'kotak hitam' yang tidak mendedahkan kebolehupayaan algoritma metaheuristik hanya menyelesaikan masalah tertentu dan tidak menyeluruh dalam semua penyelesaian. Bagi menangani jurang yang ketara antara teori dan amalan dalam penyelidikan metaheuristik, kajian ini mencadangkan pendekatan analisis mendalam menggunakan komponen algoritma metaheuristik dan pengukuran kepelbagaian untuk menentukan keupayaan penerokaan dan eksploitasi. Kajian ini memilih tiga algoritma metaheuristik iaitu Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), dan Cuckoo Cuckoo (CS) untuk melaksanakan analisis komponen yang lebih cekap. Hasil kajian yang dicadangkan telah membuktikan kemampuan menangani masalah penumpuan awal PSO, eksploitasi yang lemah ABC, dan isu penerokaan dan eksploitasi yang tidak seimbang CS. Dari kajian sorotan sedia ada, cadangan PSO yang lebih baik (iPSO), penambahbaikan ABC (iABC), dan peningkatan CS (iCS) termasuk Gray Wolf Optimization (GWO) dan Animal Migration Optimization (AMO) telah mengatasi kebolehupayaan algoritma dan variasi piawai berdasarkan masalah modaliti yang berbeza. Implementasi cadangan iPSO, iABC, dan iCS terhadap Fuzzy-Meta Classifier (FMC) yang baru dapat menawarkan penurunan kerumitan model dan meningkatkan ketepatan berbanding kaedah Adaptive Neuro-Fuzzy Inference System (ANFIS). Cadangan tiga lapisan FMC menghasilkan petua yang berkesan dengan ketepatan hampir 100% berdasarkan sepuluh kumpulan data klasifikasi yang terpilih, pengurangan ketara bilangan parameter yang terlatih dan bilangan nod dalam seni bina rangkaian berbanding kaedah ANFIS.

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LIST OF SYMBOLS AND ABBREVIATIONS

p	-	Optimization problem
S	-	Search space
Ω	-	Set of constraints
f	-	Objective function
MOP	-	Multi-objective optimization problem
COP	-	Combinatorial optimization problem
CP	-	Constrained optimization problem
D	-	Problem dimensions
Xpl	-	Exploration
Xpt	-	Exploitation
C_1, C_2	-	Acceleration coefficients of PSO
P_a	-	Switching parameter in CS
a	-	Levy flight step length
$Rand$	-	Random variable
PSO	-	Particle Swarm Optimization
ABC	-	Artificial Bee Colony
CS	-	Cuckoo Search
COG	-	Cognitive component in PSO
SOC	-	Social component in PSO
INER	-	Inertia component in PSO
EB	-	Employed bee component in ABC
OB	-	Onlooker bee component in ABC
SB	-	Scout bee component in ABC
LF	-	Levy flight component in CS
DISC	-	Discovery component in CS

LIST OF PUBLICATIONS

Hussain, K., Salleh, M. N. M., Cheng S., & Shi, Y. (2018). Metaheuristic Research: A Comprehensive Survey. *Artificial Intelligence Review*, 1-43. Springer

Hussain, K., Salleh, M. N. M., Cheng S., & Shi, Y. (2018). On the exploration and exploitation of popular swarm-based metaheuristic algorithms. *Neural Computing and Applications*, 1-19. Springer.

Hussain, K., Salleh, M. N. M., Cheng S., Shi, Y., Naseem, R. (2018). Artificial bee colony: A component-wise analysis using diversity measurement. *Journal of King Saud University - Computer and Information Sciences*, Elsevier. [In Revision].

Hussain, K., Salleh, M. N. M., Cheng, S., Almonacid, B., Talpur, N. (2018). Metaheuristic Performance Analysis by Exploration and Exploitation Measurement, *International Journal of Advances in Soft Computing and Its Application*, Universiti Technology Malaysia, Malaysia. [Under Review]

Salleh, M. N. M., **Hussain, K.**, & Talpur, N. (2018, August). A Divide and Conquer Strategy for Adaptive Neuro-Fuzzy Inference System Learning using Metaheuristic Algorithms. In *International Conference on Intelligent and Interactive Computing (IIC 2018)*. Springer.

Talpur, N., Salleh, M. N. M., & **Hussain, K.** (2018, November). Modified ANFIS with less model complexity for classification problems. In *International Conference on Computational Intelligence in Information Systems (CIIS 2018)*. Springer.

Hussain, K., & Salleh, M. N. M. (2018). Personal Best Cuckoo Search Algorithm for Global Optimization, *International Journal on Advanced Science, Engineering and Information Technology*, INSIGHT, Indonesia. [Accepted]

Salleh, M. N. M., Talpur, N., **Hussain, K.** (2018). A Modified Neuro-Fuzzy System Using Metaheuristic Approaches for Data Classification, *Artificial Intelligence – Emerging Trends and Applications (pp. 29-45),* London: IntechOpen.

Salleh, M. N. M., Hassan, N., **Hussain, K**., Talpur, N., & Cheng, S. (2018, March). Modified Adaptive Neuro-Fuzzy Inference System Trained by Scoutless Artificial Bee Colony. In *Future of Information and Communications Conference (FICC 2018)*. IEEE.

Salleh, M. N. M., **Hussain, K.**, Cheng, S., Shi, Y., Muhammad, A., Ullah, G., & Naseem, R. (2018, February). Exploration and Exploitation Measurement in Swarm-Based Metaheuristic Algorithms: An Empirical Analysis. In *International Conference on Soft Computing and Data Mining* (SCDM 2018) (pp. 24-32). Springer.

Hussain, K., Salleh, M. N. M., Hassan, N., & Cheng, S. (2017). Common Benchmark Functions for Metaheuristic Evaluation: A Review. *JOIV: International Journal on Informatics Visualization*. 1(4-2), 218-223

Salleh, M. N. M., & **Hussain, K.** (2017). Optimization of Fuzzy Neural Networks using Mine Blast Algorithm for Classification Problem. *Transactions on Machine Learning and Artificial Intelligence*, 5(5), 01.

Talpur, N., & Salleh, M. N. M., & **Hussain, K.** (2017, August). An investigation of membership functions on performance of ANFIS for solving classification problems. In *IOP Conference Series: Materials Science and Engineering* (Vol. 226, No. 1, p. 012103). IOP Publishing.

Hussain, K., Salleh, M. N. M., Cheng, S., & Shi, Y. (2017, July). Comparative Analysis of Swarm-Based Metaheuristic Algorithms on Benchmark Functions. In *International Conference in Swarm Intelligence* (pp. 3-11). Springer.

Talpur, N., & Salleh, M. N. M., & **Hussain, K.** (2017, July). Adaptive Neuro-Fuzzy Inference System: Overview, Strengths, Limitations, and Solutions. In *International Conference on Data Mining and Big Data* (pp. 527-535). Springer, Cham.

Hussain, K., Salleh, M. N. M., Naseem, R., & Uddin, J. (2016, August). Optimization of ANFIS Using Artificial Bee Colony Algorithm for Classification of Malaysian SMEs. In *International Conference on Soft Computing and Data Mining* (pp. 21-30). Springer.

Hussain, K., Hassan, N., & Ghazali, R. (2016, August). Training ANFIS Using Catfish-Particle Swarm Optimization for Classification. In *International Conference on Soft Computing and Data Mining* (pp. 201-210). Springer.

CHAPTER 1

INTRODUCTION

Computation has been so pervasive in our daily routine that we sometimes do not even realize while using it. From a tiny electronic gadget in our hands to the super systems controlling space shuttles utilize computing so intelligently that we could hardly imagine in past. Today, computational intelligence (CI) keeps airplanes in the air, driver-less cars on the road, and even simply washing clothes. CI plays vital role in computational problem solving that involves large data and enormous computation to make efficient and intelligent decisions. The popular CI techniques include artificial neural network (ANN), fuzzy logic, and evolutionary algorithms, which adhere to the basic requirements of intelligence: comprehend, reason, learn, and make intelligent decision. Such intelligent techniques are aimed at solving ill-defined, complex, nonlinear, and dynamic problems by choosing the best one from the large choice of available solutions to a given problem. Because, the size of solutions is large, these techniques couple with optimization methods, called metaheuristic algorithms, to choose the best solution (Zhang *et al.*, 2015).

In CI techniques, neuro-fuzzy systems have earned more success as compared to neural networks and support vector machines etc., mostly because of accuracy in data approximation and ability to deal with uncertainty (Arshad *et al.*, 2013). Among other neuro-fuzzy systems is adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993) which has shown significant generalization capability than other neural networks and statistical methods in variety of applications (Bardestani *et al.*, 2017; Faustino *et al.*, 2014; Zamani *et al.*, 2015). However, the applications with large input size halt ANFIS implementation due to curse of dimensionality. To address this, ANFIS is incorporated with other techniques such as clustering methods (Cai, 2017), support vector machine (Azadeh *et al.*, 2013) to generate smaller number of rules; on the other hand, ANFIS architecture has also been modified to produce accurate results with less computational cost (Peymanfar *et al.*, 2007). Nonetheless, the model complexity still downturns wider applicability of the system. This leads to motivation for developing simple and as efficient classifier based on motivation from fuzzy logic and neural network. This research is aimed at proposing a novel classification model that utilizes effective data interpretability of fuzzy logic, learning capability of neural networks, and efficient optimization ability of the modern metaheuristic algorithms. Since the proposed classification model is simple and efficient, hence it offers opportunities to solve classification problems with large input-size.

The motivation and background of this research is briefed in Section 1.1, followed by Section 1.2 which defines the problem statement. The aims and objectives of the study are presented in Section 1.3 and 1.4, respectively. Section 1.5 determines the scope of the research, while significance is highlighted by Section 1.6. The schedule of this research work is presented in Section 1.7, whereas Section 1.8 provides the outline of the dissertation.

1.1 Research background

It is no exaggeration that optimization is everywhere, be it engineering design, stock market, scheduling, or transportation. Various exact and conventional methods have been used to solve optimization problems, but metaheuristics have earned more popularity; due to efficiency in searching optimal solutions with affordable computational cost (Yang, 2010b). There is established research by metaheuristic community with literature providing outstanding results on wide variety of applications, as compared to traditional statistical and gradient-based optimization methods (Cheng & Prayogo, 2014; Ervural *et al.*, 2017; Manjarres *et al.*, 2013; Zhang *et al.*, 2015). This has overwhelmingly motivated researchers to modify existing metaheuristic algorithms or invent the new methods by inspirations from nature, as well as, man-made processes. Generally, all the metaheuristic algorithms follow same basic principles: stochastic in nature using randomness in search moves, no gradient information required, problem specific tuning of parameters, and traverse search environment in iterations (Cheng & Prayogo, 2014). That said, Sörensen (2015) argues that the exorbitance in metaheuristic research is often attributed to trivial comprehension of theoretical foundations and practical evidence. Supporting the argument, Yang (2012b) contends that the research in metaheuristics is heuristic and ad-hock. Currently, there exists significant gap between theory and practice, as some of the important questions on metaheuristic performances are yet to be answered. This is detrimental to the development of the field of metaheuristics as there have appeared many "not so important contributions" or even futile metaphore-based methods that are often forgotten quickly (Sorensen *et al.*, 2017).

Despite successful implementations and superiority reported in literature, there are few general issues that need to be addressed in order to utilize metaheuristics to full potential (Boussaïd *et al.*, 2013). This raises immense need of critical and comparative analysis of metaheuristic performance over certain optimization problems. It should be primarily based on theoretical and operational approaches behind mechanisms adopted for search of optimal solutions in large search space (Blum & Roli, 2003). However, it is noteworthy that the field of metaheuristics is still to reach maturity as compared to physics, chemistry, and mathematics; more attention needs to be drawn towards in-depth understanding of metaheuristic algorithms by analysing the issues and try to answer the core question "*why certain metaheuristic algorithms perform better on certain problems and not on others?*" (Fister Jr *et al.*, 2013; Sörensen, 2015; Sorensen *et al.*, 2017). This is often supported with "no-free-lunch" theorem (Yang, 2012c), although Yang (2012b) nonetheless asserts that inner working of metaheuristic algorithms is still a "black-box". Mere high-level analyses of end results may help determine "what" happened, but the important questions of "*how*" and "*why*" raised by Sorensen *et al.* (2017), Yang (2012b), and He *et al.* (2017) require more in-depth analyses to narrow the gap between theory and practice. According to Sörensen (2015), component-based view of metaheuristic algorithms will lead to focus on specific issues related to algorithm performances.

In metaheuristics, algorithms based on swarm intelligence are gaining more success as compared to other population-based counterparts (Cheng *et al.*, 2016; Yang, 2012a). Thanks to landmark particle swarm optimization (PSO) (Eberhart & Kennedy, 1995) and ant colony optimization (ACO) (Corne *et al.*, 1999) which derived the addition of adequately increasing number of swarm-based metaheuristic algorithms – not necessarily are all efficient methods hence not achieved generous acceptance in metaheuristic community. This research considers top three swarm-based metaheuristic algorithms for in-depth analyses based on component-view and exploration and exploitation measurements using population diversity.

Data mining is an important research area in soft computing. In data mining and model approximation, several techniques have been developed which employ machine learning approaches to adapt according to the problem under consideration; for example, support vector machine, neural networks, and fuzzy neural networks. Apart from fuzzy neural networks, other models are subjected to inability of explaining the decision. Therefore, scientific models based on these techniques are rather incomprehensible and non-transparent (*black-box*) (Hussain & Salleh, 2015). Many real-life problems; such as credit risk evaluation and medical diagnosis require evaluators (e.g. financial regulator or auditors, and physicians) to comprehend and reason the decision. Hence, transparency is crucial in such matters. A fuzzy neural network such as adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993) generates rules that can explain the decision made by the system. ANFIS is highly adaptive and accurate among other fuzzy inference systems (Taylan & Karagözoğlu, 2009), hence applied in wide variety of disciplines including science, engineering, business, and education, etc. (Kar *et al.*, 2014). However, because of high model complexity and computational cost, the applications of ANFIS are often limited to problems with lesser inputs. Even small increase in the number of inputs, makes ANFIS architecture complex due to exponential rise in rules and trainable parameters; resulting in curse of dimensionality (Younes *et al.*, 2015). Many modifications have been proposed by researchers which include incorporating metaheuristic algorithms to replace gradient based learning (Karaboga & Kaya, 2013; Nhu *et al.*, 2013; Pousinho *et al.*, 2012; Rini *et al.*, 2013; Younes *et al.*, 2015), model structure modifications (Faustino *et al.*, 2014; Peymanfar *et al.*, 2007), and rule-base minimization (Eftekhari & Katebi, 2008; Panella, 2012), etc.

Mostly in literature, researchers have embedded feature selection techniques to reduce input-size or clustering algorithms to reduce rule-base. This makes ANFIS applications more complex. The current study proposes a novel classification algorithm to address both the issues of model complexity and computational cost. The proposed classifier utilizes data interpretability of fuzzy logic, rule generation capability of inference system, and optimization efficiency of metaheuristic algorithms. The core benefit of the proposed classifier lies in optimizing its parameters through metaheuristic algorithms, as these algorithms have proved efficiency in solving optimization problems.

Based on the research motivation discussed earlier, the subsequent section presents the statement of the problem pertaining to current research.

1.2 Problem statement

Today's complex real-life problems are often solved by techniques coupled with metaheuristic algorithms, to find the best from large number of available solutions (Yang, 2010b). Generally, the success of metaheuristic algorithms over exact methods is attributed to effective search mechanisms adopted from natural or man-made processes. In these approaches are swarm behaviours found in natural organisms demonstrating highly intelligent social interactions, to best survive in a given environment. Swarm-based metaheuristic algorithms have earned more success as compared to other population-based counterparts (Cheng *et al.*, 2016). However, there remain significantly important unanswered questions that develop gap between theory and practice. Metaheuristic research is generally found with high-level analyses of end results – unable to address "black-box" issue of the algorithm performances (Fister Jr. *et al.*, 2013). The in-depth analysis of individual metaheuristic components will lead to address problems in weak components, to effectively modify for performance improvement (He *et al.*, 2017; Sörensen, 2015).

Among the most successful swarm-based metaheuristic algorithms are Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Cuckoo Search (CS). Despite success, each of these algorithms maintains certain shortcomings. PSO suffers from premature convergence due to lack of diversity, ABC has poor exploitation ability because of extraordinary randomness in scout bees, and CS bears imbalanced exploration and exploitation caused by inconsistent swarm behaviour. This research performed in-depth analysis on PSO, ABC, and CS using component-wise approach to address the aforementioned issues. The proposed component-wise approach helped answer the crucial performance related questions pertaining to "*why*" and "*how*" instead of just "*what*" happened. The analyses are

REFERENCES

Abedinia, O., Amjady, N., & Ghasemi, A. (2016). A new metaheuristic algorithm based on shark smell optimization. *Complexity, 21*(5), 97-116.

Adekanmbi, O., & Green, P. (2015). Conceptual Comparison of Population Based Metaheuristics for Engineering Problems. *The Scientific World Journal, 2015*, 9.

Akay, B., & Karaboga, D. (2012). A modified artificial bee colony algorithm for real-parameter optimization. *Information Sciences, 192*, 120-142.

Akrami, S. A., El-Shafie, A., & Jaafar, O. (2013). Improving rainfall forecasting efficiency using modified adaptive Neuro-Fuzzy Inference System (MANFIS). *Water resources management, 27*(9), 3507-3523.

Alcalá-Fdez, J., Sanchez, L., Garcia, S., del Jesus, M. J., Ventura, S., Garrell, J. M., . . . Rivas, V. M. (2009). KEEL: a software tool to assess evolutionary algorithms for data mining problems. *Soft Computing-A Fusion of Foundations, Methodologies and Applications, 13*(3), 307-318.

Arasomwan, A. M., & Adewumi, A. O. (2014). An investigation into the performance of particle swarm optimization with various chaotic maps. *Mathematical Problems in Engineering, 2014*, 17

Arshad, R. R., Sayyad, G., Mosaddeghi, M., & Gharabaghi, B. (2013). Predicting saturated hydraulic conductivity by artificial intelligence and regression models. *ISRN Soil Science, 2013*, 8.

Azadeh, A., Saberi, M., Kazem, A., Ebrahimipour, V., Nourmohammadzadeh, A., & Saberi, Z. (2013). A flexible algorithm for fault diagnosis in a centrifugal pump with corrupted data and noise based on ANN and support vector machine with hyper-parameters optimization. *Applied Soft Computing, 13*(3), 1478-1485.

Bae, C., Yeh, W.-C., Wahid, N., Chung, Y. Y., & Liu, Y. (2012). A new simplified swarm optimization (SSO) using exchange local search scheme. *International Journal of Innovative Computing, Information and Control*, *8*(6), 4391-4406.

Bardestani, S., Givehchi, M., Younesi, E., Sajjadi, S., Shamshirband, S., & Petkovic, D. (2017). Predicting turbulent flow friction coefficient using ANFIS technique. *Signal, Image and Video Processing*, *11*(2), 341-347.

Blum, C., & Roli, A. (2003). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM Computing Surveys (CSUR)*, *35*(3), 268-308.

Bouhmala, N. (2015). A Variable Depth Search Algorithm for Binary Constraint Satisfaction Problems. *Mathematical Problems in Engineering*, *2015*. doi:10.1155/2015/637809

Boussaïd, I., Lepagnot, J., & Siarry, P. (2013). A survey on optimization metaheuristics. *Information Sciences*, *237*, 82-117.

Cai, Y. (2017). Modeling for the Calcination Process of Industry Rotary Kiln Using ANFIS Coupled with a Novel Hybrid Clustering Algorithm. *Mathematical Problems in Engineering*, *2017*, 8. doi:10.1155/2017/1067351

Chang, C.-C., & Lin, C.-J. (2011). LIBSVM: a library for support vector machines. *ACM transactions on intelligent systems and technology (TIST)*, *2*(3), 27.

Chen, W.-N., Zhang, J., Lin, Y., Chen, N., Zhan, Z.-H., Chung, H. S.-H., . . . Shi, Y.-H. (2013). Particle swarm optimization with an aging leader and challengers. *IEEE transactions on evolutionary computation*, *17*(2), 241-258.

Cheng, M.-Y., & Prayogo, D. (2014). Symbiotic Organisms Search: A new metaheuristic optimization algorithm. *Computers & Structures*, *139*, 98-112.

Cheng, S. (2013). Population diversity in particle swarm optimization: Definition, observation, control, and application. *University of Liverpool, England*.

Cheng, S., & Shi, Y. (2011, April). *Diversity control in particle swarm optimization.* Paper presented at the 2011 IEEE Symposium on Swarm Intelligence (SIS), Paris.

Cheng, S., Shi, Y., Qin, Q., Zhang, Q., & Bai, R. (2014). Population diversity maintenance in brain storm optimization algorithm. *Journal of Artificial Intelligence and Soft Computing Research*, *4*(2), 83-97.

Cheng, S., Zhang, Q., & Qin, Q. (2016). Big data analytics with swarm intelligence. *Industrial Management & Data Systems*, *116*(4), 646-666.

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

Corne, D., Dorigo, M., Glover, F., Dasgupta, D., Moscato, P., Poli, R., & Price, K. V. (1999). *New ideas in optimization*: McGraw-Hill Ltd., UK.

Črepinšek, M., Liu, S.-H., & Mernik, M. (2013). Exploration and exploitation in evolutionary algorithms: a survey. *ACM Computing Surveys (CSUR), 45*(3), 35.

Doğan, B., & Ölmez, T. (2015). A new metaheuristic for numerical function optimization: Vortex Search algorithm. *Information Sciences, 293*, 125-145.

Eberhart, R. C., & Kennedy, J. (1995, October). *A new optimizer using particle swarm theory*. Paper presented at the Proceedings of the sixth international symposium on micro machine and human science, Nagoya.

Eftekhari, M., & Katebi, S. (2008). Extracting compact fuzzy rules for nonlinear system modeling using subtractive clustering, GA and unscented filter. *Applied Mathematical Modelling, 32*(12), 2634-2651.

Ervural, B., Ervural, B. C., & Kahraman, C. (2017). A Comprehensive Literature Review on Nature-Inspired Soft Computing and Algorithms: Tabular and Graphical Analyses *Handbook of Research on Soft Computing and Nature-Inspired Algorithms* (pp. 34-68): IGI Global.

Esmaeili, M., Osanloo, M., Rashidinejad, F., Bazzazi, A. A., & Taji, M. (2014). Multiple regression, ANN and ANFIS models for prediction of backbreak in the open pit blasting. *Engineering with computers, 30*(4), 549-558.

Faustino, C. P., Novaes, C. P., Pinheiro, C. A. M., & Carpinteiro, O. A. (2014). Improving the performance of fuzzy rules-based forecasters through application of FCM algorithm. *Artificial Intelligence Review*, *41*(2), 287-300.

Feo, T. A., & Resende, M. G. (1989). A probabilistic heuristic for a computationally difficult set covering problem. *Operations research letters*, *8*(2), 67-71.

Fister, I., Yang, X.-S., & Brest, J. (2013). A comprehensive review of firefly algorithms. *Swarm and Evolutionary Computation, 13*, 34-46.

Fister Jr, I., Yang, X.-S., Fister, I., Brest, J., & Fister, D. (2013). A brief review of nature-inspired algorithms for optimization. *arXiv preprint arXiv:1307.4186*.

Freitas, A. A. (2013). *Data mining and knowledge discovery with evolutionary algorithms*: Springer Science & Business Media.

Geem, Z. W., Kim, J. H., & Loganathan, G. V. (2001). A new heuristic optimization algorithm: harmony search. *simulation, 76*(2), 60-68.

Ghosh, S., Biswas, S., Sarkar, D., & Sarkar, P. P. (2014). A novel Neuro-fuzzy classification technique for data mining. *Egyptian Informatics Journal, 15*(3), 129-147.

Glover, F. (1989). Tabu search—part I. *ORSA Journal on computing, 1*(3), 190-206.

Gong, Y.-J., Li, J.-J., Zhou, Y., Li, Y., Chung, H. S.-H., Shi, Y.-H., & Zhang, J. (2016). Genetic learning particle swarm optimization. *IEEE transactions on cybernetics, 46*(10), 2277-2290.

Gorunescu, F. (2011). *Data Mining: Concepts, models and techniques* (Vol. 12): Springer Science & Business Media.

He, X., Yang, X.-S., Karamanoglu, M., & Zhao, Y. (2017). Global convergence analysis of the flower pollination algorithm: a Discrete-Time Markov Chain Approach. *Procedia Computer Science, 108*, 1354-1363.

Hemanth, D. J., Balas, V. E., & Anitha, J. (2016). Hybrid Neuro-Fuzzy Approaches for Abnormality Detection in Retinal Images *Soft Computing Applications* (pp. 295-305): Springer.

Holland, J. H. (1992). Genetic algorithms. *Scientific american, 267*(1), 66-73.

Hüllermeier, E. (2015). Does machine learning need fuzzy logic? *Fuzzy Sets and Systems, 281*, 292-299.

Hussain, K., & Salleh, M. N. M. (2015, June). *Optimization of fuzzy neural network using APSO for predicting strength of Malaysian SMEs.* Paper presented at the Control Conference (ASCC), Kota Kinabalu, 2015 10th Asian.

Iordache, S. (2010). *Consultant-guided search: a new metaheuristic for combinatorial optimization problems.* Paper presented at the Proceedings of the 12th annual conference on Genetic and evolutionary computation.

Iraji, M. S. (2017). Multi-layer architecture for adaptive fuzzy inference system with a large number of input features. *Cognitive Systems Research, 42*(C), 23-41.

James, J., & Li, V. O. (2015). A social spider algorithm for global optimization. *Applied Soft Computing, 30*, 614-627.

Jang, J.-S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics, 23*(3), 665-685.

Jarboui, B., Siarry, P., Teghem, J., & Bourrieres, J.-P. (2013). *Metaheuristics for production scheduling*: Wiley Online Library.

Jayawardena, A., Perera, E., Zhu, B., Amarasekara, J., & Vereivalu, V. (2014). A comparative study of fuzzy logic systems approach for river discharge prediction. *Journal of hydrology, 514*, 85-101.

Joshi, A., Kulkarni, O., Kakandikar, G., & Nandedkar, V. (2017). Cuckoo Search Optimization-A Review. *Materials Today: Proceedings, 4*(8), 7262-7269.

Kar, S., Das, S., & Ghosh, P. K. (2014). Applications of neuro fuzzy systems: A brief review and future outline. *Applied Soft Computing, 15*, 243-259.

Kar, S., & Majumder, D. D. (2017). An Investigative Study on Early Diagnosis of Prostate Cancer Using Neuro-Fuzzy Classification System for Pattern Recognition. *International Journal of Fuzzy Systems, 19*(2), 423-439.

Karaboga, D. (2005). *An idea based on honey bee swarm for numerical optimization* (Technical report-tr06). Retrieved from Erciyes university, engineering faculty, computer engineering department:

Karaboga, D., & Akay, B. (2009). A comparative study of artificial bee colony algorithm. *Applied Mathematics and Computation, 214*(1), 108-132.

Karaboga, D., Gorkemli, B., Ozturk, C., & Karaboga, N. (2014). A comprehensive survey: artificial bee colony (ABC) algorithm and applications. *Artificial Intelligence Review, 42*(1), 21-57.

Karaboga, D., & Kaya, E. (2013, June). *Training ANFIS using artificial bee colony algorithm.* Paper presented at the Innovations in Intelligent Systems and Applications (INISTA), Albena, 2013 IEEE International Symposium on.

Kaveh, A., & Farhoudi, N. (2016). Dolphin monitoring for enhancing metaheuristic algorithms: Layout optimization of braced frames. *Computers & Structures, 165*, 1-9.

Khachaturyan, A., Semenovsovskaya, S., & Vainshtein, B. (1981). The thermodynamic approach to the structure analysis of crystals. *Acta Crystallographica Section A: Crystal Physics, Diffraction, Theoretical and General Crystallography, 37*(5), 742-754.

Khajehzadeh, M., Taha, M. R., El-Shafie, A., & Eslami, M. (2011). A survey on meta-heuristic global optimization algorithms. *Research Journal of Applied Sciences, Engineering and Technology, 3*(6), 569-578.

Khoshnevisan, B., Rafiee, S., Omid, M., & Mousazadeh, H. (2014). Development of an intelligent system based on ANFIS for predicting wheat grain yield on the basis of energy inputs. *Information processing in agriculture, 1*(1), 14-22.

Kim, J. H., Ngo, T. T., & Sadollah, A. (2016). *A new collaborative approach to particle swarm optimization for global optimization.* Paper presented at the Proceedings of Fifth International Conference on Soft Computing for Problem Solving.

Ktari, R., & Chabchoub, H. (2013). Essential particle swarm optimization queen with tabu search for MKP resolution. *Computing, 95*(9), 897-921.

Kuo, R.-J., Chen, C., Liao, T. W., & Tien, F. (2013). Hybrid of artificial immune system and particle swarm optimization-based support vector machine for Radio Frequency Identification-based positioning system. *Computers & Industrial Engineering, 64*(1), 333-341.

Kuo, R., & Hong, C. (2013). Integration of genetic algorithm and particle swarm optimization for investment portfolio optimization. *Applied Mathematics & Information Sciences, 7*(6), 2397.

Li, M. D., Zhao, H., Weng, X. W., & Han, T. (2016). A novel nature-inspired algorithm for optimization: Virus colony search. *Advances in Engineering Software, 92*, 65-88.

Li, S.-X., & Wang, J.-S. (2015). Dynamic Modeling of Steam Condenser and Design of PI Controller Based on Grey Wolf Optimizer. *Mathematical Problems in Engineering, 2015*, 9.

Li, W., Wang, L., Yao, Q., Jiang, Q., Yu, L., Wang, B., & Hei, X. (2015). Cloud Particles Differential Evolution Algorithm: A Novel Optimization Method for Global Numerical Optimization. *Mathematical Problems in Engineering, 2015*, 36.

Li, X., Wang, J., & Yin, M. (2014). Enhancing the performance of cuckoo search algorithm using orthogonal learning method. *Neural Computing and Applications, 24*(6), 1233-1247.

Li, X., Yang, H., Yang, M., Yang, X., & Yang, G. (2017, June). *Accelerating artificial bee colony algorithm with neighborhood search.* Paper presented at the Evolutionary Computation (CEC), San Sebastian, 2017 IEEE Congress on.

Li, X., & Yin, M. (2016). A particle swarm inspired cuckoo search algorithm for real parameter optimization. *Soft Computing, 20*(4), 1389-1413.

Li, X., Zhang, J., & Yin, M. (2014). Animal migration optimization: an optimization algorithm inspired by animal migration behavior. *Neural Computing and Applications, 24*(7-8), 1867-1877.

Lichman, M. (2013). UCI Machine Learning Repository. *University of California, Irvine, School of Information and Computer Sciences*.

Lim, W. H., & Isa, N. A. M. (2014). Bidirectional teaching and peer-learning particle swarm optimization. *Information Sciences, 280*, 111-134.

Liu, P., Leng, W., & Fang, W. (2013). Training anfis model with an improved quantum-behaved particle swarm optimization algorithm. *Mathematical Problems in Engineering, 2013*.

Liu, S., Crepinsek, M., & Mernik, M. (2012). *Analysis of VEGA and SPEA2 using exploration and exploitation measures.* Paper presented at the Proceedings of the 5th International Conference on Bio-inspired Optimization Methods and Their Applications, Bohinj.

Loganathan, C., & Girija, K. (2014). Investigations on hybrid learning in ANFIS. *International Journal of Engineering Research and Applications, 4*(10), 31-37.

Mahdavi, S., Shiri, M. E., & Rahnamayan, S. (2015). Metaheuristics in large-scale global continues optimization: a survey. *Information Sciences, 295*, 407-428.

Manjarres, D., Landa-Torres, I., Gil-Lopez, S., Del Ser, J., Bilbao, M. N., Salcedo-Sanz, S., & Geem, Z. W. (2013). A survey on applications of the harmony search algorithm. *Engineering Applications of Artificial Intelligence, 26*(8), 1818-1831.

Marinakis, Y., Marinaki, M., & Matsatsinis, N. (2009, June). *A hybrid bumble bees mating optimization-grasp algorithm for clustering.* Paper presented at the International Conference on Hybrid Artificial Intelligence Systems, Salamanca.

Meher, S. K. (2017). Efficient pattern classification model with neuro-fuzzy networks. *Soft Computing, 21*(12), 3317-3334.

Mirjalili, S. (2015). Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. *Knowledge-Based Systems, 89*, 228-249.

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in Engineering Software, 69*, 46-61.

Mladenović, N., & Hansen, P. (1997). Variable neighborhood search. *Computers & operations research, 24*(11), 1097-1100.

Mohammed, S. H. A. A., & Mustafa, Z. A. (2017). Breast Tumors Classification Using Adaptive Neuro-Fuzzy Inference System. *Journal of Clinical Engineering, 42*(2), 68-72.

Nhu, H. N., Nitsuwat, S., & Sodanil, M. (2013, September). *Prediction of stock price using an adaptive Neuro-Fuzzy Inference System trained by Firefly Algorithm.* Paper presented at the Computer Science and Engineering Conference (ICSEC), Nakorn Pathom, 2013 International.

Ong, P. (2014). Adaptive cuckoo search algorithm for unconstrained optimization. *The Scientific World Journal, 2014*, 8.

Pan, W.-T. (2012). A new fruit fly optimization algorithm: taking the financial distress model as an example. *Knowledge-Based Systems, 26*, 69-74.

Panella, M. (2012). A hierarchical procedure for the synthesis of ANFIS networks. *Advances in Fuzzy Systems, 2012*, 20.

Peymanfar, A., Khoei, A., & Hadidi, K. (2007, December). *A new ANFIS based learning algorithm for CMOS neuro-fuzzy controllers.* Paper presented at the Electronics, Circuits and Systems (ICECS) 2007. 14th IEEE International Conference on, Marrakech.

Pham, D. T., & Huynh, T. T. B. (2015). *An Effective Combination of Genetic Algorithms and the Variable Neighborhood Search for Solving Travelling Salesman Problem.* Paper presented at the Technologies and Applications of Artificial Intelligence (TAAI), 2015 Conference on.

Pousinho, H. M. I., Mendes, V. M. F., & Catalão, J. P. d. S. (2012). Short-term electricity prices forecasting in a competitive market by a hybrid PSO–ANFIS approach. *International Journal of Electrical Power & Energy Systems, 39*(1), 29-35.

Puchinger, J., & Raidl, G. R. (2005). *Combining metaheuristics and exact algorithms in combinatorial optimization: A survey and classification.* Paper presented at the International Work-Conference on the Interplay Between Natural and Artificial Computation.

Qin, Q., Cheng, S., Zhang, Q., Li, L., & Shi, Y. (2015). Artificial bee colony algorithm with time-varying strategy. *Discrete Dynamics in Nature and Society, 2015*, 17

Rakhshani, H., & Rahati, A. (2017). Snap-drift cuckoo search: A novel cuckoo search optimization algorithm. *Applied Soft Computing, 52,* 771-794.

Rao, R. V., Savsani, V. J., & Vakharia, D. (2011). Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. *Computer-Aided Design, 43*(3), 303-315.

Rini, D. P., Shamsuddin, S. M., & Yuhaniz, S. S. (2013). Balanced the trade-offs problem of anfis using particle swarm optimisation. *TELKOMNIKA (Telecommunication Computing Electronics and Control), 11*(3), 611-616.

Sahli, Z., Hamouda, A., Bekrar, A., & Trentesaux, D. (2014, November). *Hybrid PSO-Tabu search for the optimal reactive power dispatch problem.* Paper presented at the 40th Annual Conference of the IEEE Industrial Electronics Society, Dallas.

Salcedo-Sanz, S., Del Ser, J., Landa-Torres, I., Gil-López, S., & Portilla-Figueras, J. (2014). The coral reefs optimization algorithm: a novel metaheuristic for efficiently solving optimization problems. *The Scientific World Journal, 2014*.

Salimi, H. (2015). Stochastic fractal search: a powerful metaheuristic algorithm. *Knowledge-Based Systems, 75,* 1-18.

Salleh, M. N. M., & Hussain, K. (2016). A Review of Training Methods of ANFIS for Applications in Business and Economics. *International Journal of u-and e-Service, Science and Technology, 9*(7), 165-172.

Salleh, M. N. M., Talpur, N., & Hussain, K. (2017, June). *Adaptive Neuro-Fuzzy Inference System: Overview, Strengths, Limitations, and Solutions.* Paper presented at the International Conference on Data Mining and Big Data (DMBC 2017), JR Hakata.

Shehab, M., Khader, A. T., & Al-Betar, M. A. (2017). A survey on applications and variants of the cuckoo search algorithm. *Applied Soft Computing, 61*(12), 1041-1059.

Shi, Y., & Eberhart, R. (1998). *A modified particle swarm optimizer.* Paper presented at the Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., The 1998 IEEE International Conference on.

Shi, Y., & Eberhart, R. C. (2008). *Population diversity of particle swarms.* Paper presented at the Evolutionary Computation, 2008. CEC 2008.(IEEE World Congress on Computational Intelligence). IEEE Congress on.

Siddique, N., & Adeli, H. (2013). *Computational intelligence: synergies of fuzzy logic, neural networks and evolutionary computing*: John Wiley & Sons.

Simon, D. (2008). Biogeography-based optimization. *IEEE transactions on evolutionary computation, 12*(6), 702-713.

Sörensen, K. (2015). Metaheuristics—the metaphor exposed. *International Transactions in Operational Research, 22*(1), 3-18.

Sörensen, K., Maya Duque, P., Vanovermeire, C., & Castro, M. (2012). Metaheuristics for the Multimodal Optimization of Hazmat Transports. *Security Aspects of Uni-and Multimodal Hazmat Transportation Systems*, 163-181.

Sorensen, K., Sevaux, M., & Glover, F. (2017). A history of metaheuristics. *arXiv preprint arXiv:1704.00853*.

Storn, R., & Price, K. (1997). Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization, 11*(4), 341-359.

Stützle, T. (1998). Local search algorithms for combinatorial problems. *Darmstadt University of Technology PhD Thesis, 20*.

Sun, W., & Yuan, Y.-X. (2006). *Optimization theory and methods: nonlinear programming* (Vol. 1): Springer Science & Business Media.

Taherkhani, M., & Safabakhsh, R. (2016). A novel stability-based adaptive inertia weight for particle swarm optimization. *Applied Soft Computing, 38*, 281-295.

Talbi, E. G., Basseur, M., Nebro, A. J., & Alba, E. (2012). Multi-objective optimization using metaheuristics: non-standard algorithms. *International Transactions in Operational Research, 19*(1-2), 283-305.

Tan, Y., & Zhu, Y. (2010). Fireworks algorithm for optimization. *Advances in swarm intelligence*, 355-364.

Taylan, O., & Karagözoğlu, B. (2009). An adaptive neuro-fuzzy model for prediction of student's academic performance. *Computers & Industrial Engineering, 57*(3), 732-741.

Wahab, M. N. A., Nefti-Meziani, S., & Atyabi, A. (2015). A comprehensive review of swarm optimization algorithms. *PloS one, 10*(5), e0122827.

Walia, N., Singh, H., & Sharma, A. (2015). ANFIS: Adaptive Neuro-Fuzzy Inference System-A Survey. *International Journal of Computer Applications, 123*(13), 32-38.

Wang, H., Sun, H., Li, C., Rahnamayan, S., & Pan, J.-S. (2013). Diversity enhanced particle swarm optimization with neighborhood search. *Information Sciences, 223*, 119-135.

Wang, Y. (2010). A Sociopsychological Perspective on Collective Intelligence in Metaheuristic Computing.

Wei, Z. (2013). A Raindrop Algorithm for Searching The Global Optimal Solution in Non-linear Programming. *arXiv preprint arXiv:1306.2043*.

Xiang, W.-l., Li, Y.-z., Meng, X.-l., Zhang, C.-m., & An, M.-q. (2017). A grey artificial bee colony algorithm. *Applied Soft Computing*.

Xue, Y., Jiang, J., Zhao, B., & Ma, T. (2017). A self-adaptive artificial bee colony algorithm based on global best for global optimization. *Soft Computing*, 1-18.

Yang, F.-C., & Wang, Y.-P. (2007). Water flow-like algorithm for object grouping problems. *Journal of the Chinese Institute of Industrial Engineers, 24*(6), 475-488.

Yang, X.-S. (2010a). Firefly algorithm, Levy flights and global optimization. *Research and development in intelligent systems XXVI*, 209-218.

Yang, X.-S. (2010b). *Nature-inspired metaheuristic algorithms*: Luniver press.

Yang, X.-S. (2010c). A new metaheuristic bat-inspired algorithm. *Nature inspired cooperative strategies for optimization (NICSO 2010)*, 65-74.

Yang, X.-S. (2011a). Metaheuristic optimization: algorithm analysis and open problems *Experimental Algorithms* (pp. 21-32): Springer.

Yang, X.-S. (2012a). Efficiency analysis of swarm intelligence and randomization techniques. *Journal of Computational and Theoretical Nanoscience, 9*(2), 189-198.

Yang, X.-S. (2012b). Nature-inspired mateheuristic algorithms: Success and new challenges. *arXiv preprint arXiv:1211.6658*.

Yang, X.-S. (2012c). Swarm-based metaheuristic algorithms and no-free-lunch theorems *Theory and New Applications of Swarm Intelligence*: InTech.

Yang, X.-S. (2014). Swarm intelligence based algorithms: a critical analysis. *Evolutionary intelligence, 7*(1), 17-28.

Yang, X.-S. (2018). Mathematical Analysis of Nature-Inspired Algorithms *Nature-Inspired Algorithms and Applied Optimization* (pp. 1-25): Springer.

Yang, X.-S., Cui, Z., Xiao, R., Gandomi, A. H., & Karamanoglu, M. (2013). *Swarm intelligence and bio-inspired computation: theory and applications*: Newnes.

Yang, X.-S., & Deb, S. (2009). *Cuckoo search via Lévy flights.* Paper presented at the Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on.

Yang, X.-S., & Deb, S. (2014). Cuckoo search: recent advances and applications. *Neural Computing and Applications, 24*(1), 169-174.

Yang, X.-S., Deb, S., Hanne, T., & He, X. (2015a). Attraction and diffusion in nature-inspired optimization algorithms. *Neural Computing and Applications*, 1-8.

Yang, X.-S., & He, X. (2013). Bat algorithm: literature review and applications. *International Journal of Bio-Inspired Computation, 5*(3), 141-149.

Yang, X. S. (2011b). Metaheuristic optimization: algorithm analysis and open problems *Experimental Algorithms* (pp. 21-32): Springer.

Yang, X. S., Deb, S., Hanne, T., & He, X. (2015b). Attraction and diffusion in nature-inspired optimization algorithms. *Neural Computing and Applications*, 1-8.

Younes, M. K., Nopiah, Z., Basri, N. A., Basri, H., Abushammala, M. F., & KNA, M. (2015). Solid waste forecasting using modified ANFIS modeling. *Journal of the Air & Waste Management Association, 65*(10), 1229-1238.

Yu, X., & Gen, M. (2010). *Introduction to evolutionary algorithms*: Springer Science & Business Media.

Zadeh, L. A. (2015). Fuzzy logic—a personal perspective. *Fuzzy Sets and Systems, 281*, 4-20.

Zamani, H. A., Rafiee-Taghanaki, S., Karimi, M., Arabloo, M., & Dadashi, A. (2015). Implementing ANFIS for prediction of reservoir oil solution gas-oil ratio. *Journal of Natural Gas Science and Engineering, 25*, 325-334.

Zelinka, I. (2015). A survey on evolutionary algorithms dynamics and its complexity–Mutual relations, past, present and future. *Swarm and Evolutionary Computation, 25*, 2-14.

Zhang, Y., Wang, S., & Ji, G. (2015). A Comprehensive Survey on Particle Swarm Optimization Algorithm and Its Applications. *Mathematical Problems in Engineering, 501*, 931256.

Zhao, W., & Wang, L. (2016). An effective bacterial foraging optimizer for global optimization. *Information Sciences, 329*, 719-735.

Zheng, Y.-J. (2015). Water wave optimization: a new nature-inspired metaheuristic. *Computers & operations research*, *55*, 1-11.

Ziasabounchi, N., & Askerzade, I. (2014). ANFIS based classification model for heart disease prediction. *International Journal of Electrical & Computer Sciences IJECS-IJENS, 14*(02), 7-12.