AN ENSEMBLE OF NEURAL NETWORK AND MODIFIED GREY WOLF OPTIMIZER FOR STOCK PREDICTION

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DOCTOR OF PHILOSOPHY
(COMPUTER SCIENCE)

UNIVERSITI MALAYSIA PAHANG
SUPERVISOR’S DECLARATION

I hereby declare that I 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 Doctor of Philosophy.

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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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AN ENSEMBLE OF NEURAL NETWORK AND MODIFIED GREY WOLF OPTIMIZER FOR STOCK PREDICTION

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Pengoptimuman berkaitan dengan proses mencari penyelesaian optimum (sama ada memaksimumkan atau meminimumkan) kepada masalah tertentu yang memenuhi beberapa kekangan yang diberikan. Disebabkan kesederhanaan dan kelenturannya, meta-heuristik telah terbukti berkesan untuk menyelesaikan masalah pengoptimuman. Sehingga kini, terdapat banyak meta-heuristik yang telah dibangunkan dalam bidang penelitian. Selaras dengan teorem ‘No Free Lunch’ yang menunjukkan bahawa tiada meta-heuristik tunggal, yang terbaik untuk semua masalah pengoptimuman, tetapi mencari algoritma yang lebih baik masih merupakan usaha yang membuahtakan hasil. Grey Wolf Optimizer (GWO) merupakan algoritma meta-heuristik terkini yang menarik perhatian kebanyakan penyelidik kerana prestasi unggulnya yang disebut dalam kajian literatur. Walaupun GWO menunjukkan prestasi yang tinggi, ia juga ada kelemahannya. Pada masa kini, keoptimuman GWO adalah berat sebelah terhadap GWO jenis alfa dan jenis yang lain (iaitu beta dan delta) masing-masing cuba untuk mengubah kedudukannya ke arah yang terbaik dalam setiap proses ulangan. Proses kemaskini ini boleh menyebabkan algoritma ini bergerak ke optima tempatan terutama dalam kes-kes di mana terdapat banyak optima tempatan yang bersaing. Oleh itu, penyelidikan ini cuba mengubahsuaui GWO untuk menangani batasan GWO dengan penambahbaikan penerokaan dengan menguatkkan proses pencarian melalui beberapa pemimpin rawak dalam setiap lelaran, menghasilkan semula pemimpin rawak dalam setiap lelaran dan memperkenalkan arkib untuk mengesahkan penyelesaian dengan kebaringkalan yang lebih baik untuk teruskan latihan dan penjanaan semula. Pengesahan setiap penyelesaian secara individu oleh Modified GWO, dan bukannya dipertimbangkan sebagai penyelesaian akhir, memudahkan peningkatan penerokaan. Selain itu, penyelidikan mengehadkan bilangan pembolehubah melalui pemilihan ciri untuk meningkatkan prestasi algoritma. Selepas itu, penyelidikan cuba untuk membina model ensemble menggunakan Modified Gray Wolf Optimizer (MGWO) dan rangkaian neural untuk ramalan saham. Model-model yang meluas seperti Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Evolutionary Strategies (ES) dan Probability Based Incremental Learning (PBIL) yang berurusan dengan masalah tertentu juga diterokai dan dibandingkan. Kajian ini melaksanakan analisis ramalan saham sebagai kajian kes untuk melatih rangkaian saraf dengan mengadopsi algoritma MGWO. Dalam kajian ini, data dikumpulkan dari pasaran saham terkenal; New York Stock Exchange (NYSE), NASDAQ dan pasaran baru muncul; Dhaka Stock Exchange (DSE), Bursa Malaysia. Selain itu, pelbagai data faktor seperti harga Dolar, harga Emas, kadar faedah Bank, Pelaburan Langsung Asing, dan Inflasi dikumpulkan untuk mengukur kesan dalam pasaran saham. K-means clustering digunakan untuk memilih syarikat yang sangat menjanjikan; MGWO dilaksanakan untuk pemilihan dan latihan ciri; akhirnya, MGWO-NN digunakan untuk meramalkan harga saham. Model "ensemble" yang dipilih di sini untuk mencapai prestasi ramalan yang lebih baik, digunakan untuk meramalkan harga pasaran masa hadapan. Pendekatan yang dicadangkan mengatasi algoritma meta-heuristik sedia ada. Khususnya, model yang dicadangkan mencapai 97% kadar klasifikasi, 95% ramalan tepat dan kadar kesilapan yang kurang daripada 2.0. Sebagai kesimpulan, kejayaan pelaksanaan model MGWO dan ensemble menjadikan sumbangan yang berharga kepada arena saintifik.
ABSTRACT

Optimization relates to the process of finding the optimum solution (either maximize or minimize) to a particular problem satisfying some given constraints. Owing to its simplicity and flexibility, meta-heuristics have been proven to be effective for solving optimization problems. To date, there are many meta-heuristics have been developed in the literature. In line with the No Free Lunch theorem which suggests that no single meta-heuristic is the best for all optimization problems, the search for better algorithms is still a worthy endeavour. Grey Wolf Optimizer (GWO) is a recently developed meta-heuristic algorithm which is appealing to researcher owing to its demonstrated performance as cited in the scientific literature. Despite its performances, GWO is not without limitation. Precisely, the current best optimal individual of GWO is biased toward alpha and other individuals (e.g. beta and delta) attempt to modify their positions toward this best individual in each iteration process. This update process may cause the algorithm to fall to local optima especially in the cases where there are many competing local optima. Therefore, the research attempts to modify GWO to addresses the limitation of GWO for improvement of exploration by strengthen the searching process via several random leaders in each iteration, re-generating the random leaders in each iteration and introducing archive to verify the solution with better probability to proceed further for training and re-generation. The verification of each solution individually by Modified GWO, instead of considering as a final solution, facilitates the improvement of the exploration. Additionally, the research restricts the number of variables through feature selection to enhance the performance of the algorithm. Subsequently, the research attempts to construct an ensemble model applying Modified Grey Wolf Optimizer (MGWO) and neural network for stock prediction. Widespread models like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Evolutionary Strategy (ES) and Population-Based Incremental Learning (PBIL) dealing with the specified problems are also explored and compared. The research implements stock prediction analysis as a case study for training the neural network by adopting MGWO algorithm. In this research, data is collected from reputed stock markets; New York Stock Exchange (NYSE), NASDAQ and emerging markets; Dhaka Stock Exchange (DSE), Bursa Malaysia. Moreover, various factors data like Dollar price, Gold price, Bank interest rate, Foreign Direct Investment, and Inflation are collected to measure the effect in stock market. K-means clustering is applied to select the highly promising company; MGWO is implemented for feature selection and training; finally, MGWO-NN is applied to predict the stock price. The “ensemble” model selected here to achieve better predictive performance, is used to predict future market price. The proposed approach outperforms existing available meta-heuristic algorithms. Specifically, the proposed model achieved 97% classification rate, 95% precise prediction and less than 2.0 error rate. In conclusion, the successful implementation of MGWO and ensemble model makes a valuable contribution to scientific arena.
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LIST OF SYMBOLS

\( A \)  
Shared archived score

\( a_i \)  
Actual Price

\( A(k) \)  
Input of the Neural Network

\( d \)  
Squared Euclidean Distance

\( f \)  
Non-linear Function

\( G_{a_j} \)  
Sum of All the Best Solution

\( k \)  
Number of Clusters

\( N \)  
Average Distance between Wolves

\( p_i \)  
Predicted Price

\( P(k) \)  
Predicted Output

\( Q_i \)  
Mean

\( s \)  
Slope

\( t \)  
Number of Iteration

\( X \)  
Dataset

\( Y_{n \times k} \)  
Partition Matrix

\( \Pi \)  
Vectors
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<td>Ant Colony Optimization</td>
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<td>ANN</td>
<td>Artificial Neural Network</td>
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<td>GWO</td>
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<td>MAD</td>
<td>Mean Absolute Deviation</td>
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<td>MAPE</td>
<td>Mean Absolute Percentage Error</td>
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<td>MGWO</td>
<td>Modified Grey Wolf Optimizer</td>
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<td>NARX</td>
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<td>NFL</td>
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<td>SIV</td>
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