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Recent studies on optimisation method of Grey Wolf Optimiser (GWO): a review (2014–2017)

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Abstract Today, finding a viable solution for any real world problem focusing on combinatorial of problems is a crucial task. However, using optimisation techniques, a viable best solution for a specific problem can be obtained, developed and solved despite the existing limitations of the implemented technique. Furthermore, population based optimisation techniques are now a current interest and has spawned many new and improved techniques to rectify many engineering problems. One of these methods is the Grey Wolf Optimiser (GWO), which resembles the grey wolf's leadership hierarchy and its hunting behavior in nature. The GWO adopts the hierarchical nature of grey wolfs and lists the best solution as alpha, followed by beta and delta in descending order. Additionally, its hunting technique of tracking, encircling and attacking are also modeled mathematically to find the best optimised solution. This paper presents the results from an extensive study of 83 published papers from previous studies related to GWO in various applications such as parameter tuning, economy dispatch problem, and cost estimating to name a few. A discussion on the properties of GWO algorithm and how it minimises the different problems in the different applications is pre-

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sented, as well as an analysis on the research trend of GWO optimisation technique in various applications from year 2014 to 2017. Based on the literatures, it was observed that GWO has the ability to solve single and multi-objective problems efficiently due to its good local search criteria that performs exceptionally well for different problems and solutions.

Keywords Grey Wolf Optimiser · Optimisation · Application · Comparison · Review

1 Introduction

Optimisation is a process to find best inputs (Cheng et al. 2016) in order to obtain the maximum or minimum output (Civicioglu and Besdok 2013) with a minimum cost (Ghose 2002). This technique works by searching for the optimum solution to minimise a given problem. The optimisation process starts when the parameters, constraints, and the objective function are obtained. Then, by implementing the optimisation technique with the objective function, a minimisation will lead towards obtaining the optimum value for desired responses. In addition, there are a variety of single and multi-objective problems with various solutions to solve rectify the problems. These solutions may or may not have constrains (Jordehi and Jasni 2015) based on the suitability of the problems and the desired solutions. Most researchers used either traditional or non-traditional optimisation techniques or even both (Vardhini and Sitamahalakshmi 2016). There are various optimization techniques available such as nonlinear programming (Rakshit and Konar 2015), linear programming (Bertsimas and Tsitsiklis 1997), simulated annealing (SA) (Kirkpatrick et al. 1983), swarm intelligence (Blum and Li 2008) and etc.

The traditional optimisation technique in solving engineering problems entails the use of the gradient or direct search method for the best optimum solution. This technique is only suitable for a simple objective function and a unimodal function. For example, Taguchi Method (Mehat et al. 2013) only works best on choosing the best combination of parameter with discrete value and will become difficult when run into a multiresponse design problem. Besides, to find the optimum parameter, the combination is unidentified especially to non-expertise (Yusoff et al. 2016). Because of that, the development of non-traditional optimisation technique began growing rapidly since there is No Free Lunch (NFL) as proposed by Wolpert and Macready (1997). This theorem has already proven that there are no non-traditional or any techniques that best suited for solving all optimisation problems. Non-traditional technique is more of a natural, logical and evolutionary and has evolved and became well-known since then. Moreover, this technique is simple, flexible, easily derived and has a powerful ability to avoid local optima in minimising options of problems to search from. Nature based or swarm intelligence is an inspired optimisation algorithm and based on the simple and autonomous nature of behavior of some individual agents such as fish, ants or birds. There are established metaheuristic techniques that have been used in many fields such as Particle Swarm Optimisation (PSO) (Eberhart and Kennedy 1995), Firefly (Yang 2010), Ant Colony Optimisation (ACO) (Dorigo et al. 2006), Cuckoo Search Algorithm (Yang and Deb 2009) and recently Grey Wolf Optimiser (GWO) (Mirjalili et al. 2014).

GWO is based on grey wolves' behavior hunting mechanism and they were placed at the top of the food chain. The predators' instinct of the grey wolves is what makes this technique one of the most promising optimisation techniques. They do the hunting by living in a pack of group and follow their social hierarchy, tracking, encircling and attacking preys. Therefore, they become one of the strongest nature inspired optimisation techniques instead of other predator inspired methods. In this paper, the GWO technique in its application and the optimisation technique will be mainly reviewed. In Sect. 2, an overview of the basic concept of the GWO technique including the steps and the whole flow of the algorithm will be provided. Section 3 will include the previous studies on the application of the GWO. The paper will conclude with the discussion and future works after reviewing the GWO and its application which will be provided in Sect. 4.

2 Grey Wolf Optimiser (GWO)

Grey Wolf Optimiser (GWO) is one of the listed metaheuristic methods together with other methods namely the Particle Swarm Optimisation (PSO) (Eberhart and Kennedy 1995), Genetic Algorithm (GA) (Bonabeau et al. 1999) Artificial Neural Network (ANN) and many more. It was discovered by Mirjalili et al. (2014). This new optimisation method has shown a great result in optimising problem and has successfully beaten the well-known method such as the PSO in engineering design problem of compression spring, pressure vessel and welded beam design (Mirjalili et al. 2014). GWO has also been tested in optical buffer design to maximise the optical pulse with the highest bandwidth (Mirjalili et al. 2014).

The GWO is built based on the wolf hunting behaviors from the types of *Canis lupus* of the Canidae family. In the food chain, the grey wolf is dominating the chart as apex predators. Hence, it shows the domination of the wolf when hunting for their food/prey. The grey wolf hierarchy exists in a pack which is led by the alpha, beta, delta and omega as shown in Fig. 1. The alpha wolf, which can be either male or female grey wolf, dominates the hierarchy by being the leader in a pack. The alpha will decide on certain things especially hunting, place to sleep, waking time and many more. While the beta acts as the sidekick, it will help the alpha in making decision and will replace the alpha if anything happened to the current alpha. The delta and the omega are at the lowest rank in the grey wolf pack. Both are almost of equal type with only slight difference on their dominating character whereby the delta tends to dominate the while giving service to the alpha and the beta. The omega plays as a scapegoat in order to submit themselves to the other dominant wolves. This shows that the omega is of the least important in the pack of the wolves.

According to Muro et al. (2011) the grey wolf hunting has three main phases as shown in Fig. 2. The phases include tracking, chasing and approaching the prey. The grey wolf hunting also includes pursuing, encircling and harassing the prey until it stopped moving and attacking the prey. Based on this, the behavior of the grey wolves is then being designated by mathematical model and the optimisation is performed.

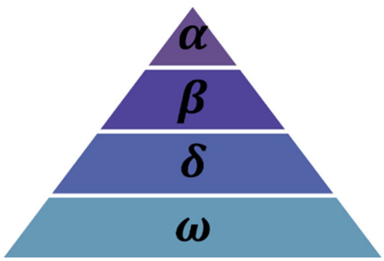

Fig. 1 The hierarchy of the grey wolf from top to bottom. (Reproduced with permission from Mirjalili et al. 2014)

Fig. 2 The hunting behavior of the grey wolves **a** chasing, approaching and tracking the prey **b**–**d** pursuing, harassing and encircling the prey **e** attacking when the prey stop moving. (Reproduced with permission from Muro et al. 2011)

2.1 Basic GWO

The mathematical model or the structure of the algorithm consists of social hierarchy, tracking, encircling and attacking prey are described further below.

2.1.1 Social hierarchy

The first element that they considered as best fit to the solution is alpha (α), beta (β) and delta (ð). The rest of the element is considered as omega (ῳ). Here, the hunting (optimisation) is controlled by α, β and ð. The ῳ wolves follow these three wolves.

2.1.2 Encircle prey

As stated before, the wolves will encircle the prey when they do the hunting. This is represented in Eqs. 1 and 2.

$$|\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{2}$$

The t indicates the current iteration, while $\vec{A}$ and $\vec{C}$ are the coefficient vectors of the prey, $\vec{X}$ represents the position of grey wolves and $\vec{X}_p$ indicates the position of the prey. Vectors $\vec{A}$ and $\vec{C}$ are presented in Eqs. 3 and 4:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{4}$$

The $\vec{a}$ elements will linearly decreased from 2 to 0 over the course of iteration and r_1, r_2 are random vectors in between [0, 1].

2.1.3 Hunting

The grey wolves' will naturally recognise the location of their prey and will usually encircle their food. This will be led by the alpha, beta and delta followed by the omega. Some of the prey's locations (optimum) searched by the wolves are not known by humans. Thus, to understand their behavior, representation of a mathematical equation was made to mimic their behaviour by assuming alpha (best candidate solution), beta and delta have a bigger knowledge about their prey's location. With that, the first three wolves were saved as the best three candidates' solution by the time being while the other wolves (omega) updated their position according to the best search candidate. The equations are shown in Eqs. 5, 6 and 7 below:

$$\vec{D}_\alpha = |\vec{C}_X \cdot \vec{X}_\alpha - \vec{X}|, \quad \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \quad \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \tag{5}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha), \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta), \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \tag{6}$$

$$\vec{X}(t+1) = \frac{\vec{x}_1 + \vec{x}_2 + \vec{x}_3}{3} \tag{7}$$

The final positions of the wolves will be at random place within a circle by the control of Eqs. 3 and 4. In addition, the alpha, beta and delta will estimate the position of the prey while the other wolves set their positions randomly around the prey.

2.1.4 Attacking prey (exploitation)

The grey wolves will finish their hunt by attacking the prey when it stops moving. The value of α and $\vec{A}$ is a decade. A is a random value in the interval $[-\alpha, \alpha]$ where it will be a limitation of the movement for the wolves to search for the prey. The searching is controlled by the decrease of the interval in α and $\vec{A}$. Where α decreases from 2 to 0 which made it nearer to the prey over the iterations.

2.1.5 Search for prey (exploration)

According to the position of alpha, beta and delta, they diverge from each other to search and converge to attack the prey. Here $\vec{A}$ is utilized as greater than 1 or less than − 1 to indicate the search agent to diverge and converge from the prey. This also emphasizes exploration and allow for GWO search globally. The whole searching process starts when any possible locations of the prey were estimated and at some point, the position and the distance of the prey will always be updated. The parameter α will be decreased to emphasize the exploration and exploitation towards the prey (optimum). The wolves will move to the prey. The wolves will then diverge and converge towards their prey. Finally, the algorithm will be withdrawn as the wolves reach their satisfaction which is when the prey's location is obtained and acknowledged by all wolves (nearest to the prey). The flowchart of the GWO is summarized in Fig. 3 below.

3 Recent studies on the application of the GWO

The application of the GWO in various fields clearly shows how effective the GWO is, even though there are some repetitions of the usage in some of the fields, but the basic GWO or hybrid or improved technique still gave better performance in solving the optimisation

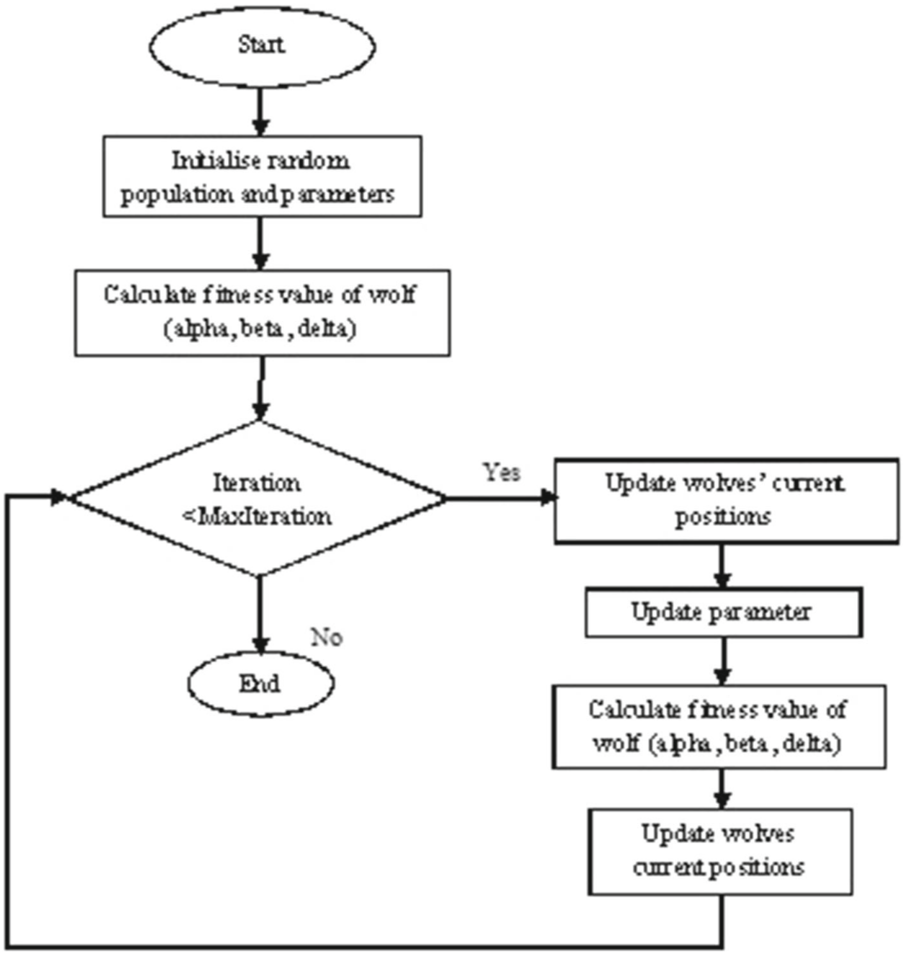

Fig. 3 The flowchart of the GWO

problems. From the previous studies, many researchers have used the GWO and applied this method in various fields such as electrical engineering (Dzung et al. 2015), gene classification (Vosooghifard and Ebrahimpour 2015), forecasting (Mustaffa et al. 2015a, b) and etc. The applications of the GWO are separated according to specific fields and are enclosed in the sections below.

3.1 Economic dispatch problems

Wong et al. (2014), applied the GWO in economic dispatch problem to obtain low transmissions loss and minimize the total fuel cost. The GWO method is being compared with the Firefly algorithm, Ant Bee Colony (ABC), Biogeography-based optimisation (BBO), Lambda Iteration (LI), Hopefield model based search (HM), Neural Network trained by ABC, Quadratic Programming (QP) and General Algebraic Modeling System (GAMS). The results showed that besides being able to achieve the aim of the study, the GWO appeared to be the most outstanding method of all. Apart from that, Sulaiman et al. (2015a) studied the GWO to solve optimum reactive power dispatch for nonlinear optimisation problem in electrical power system. The result showed that controllable variables from best combination were performed in order to achieve minimum voltage deviations.

Sulaiman et al. (2015b) investigated ways to get the minimum cost using economic dispatch problem by combining fuel-based power generation. It was revealed that the GWO was able to give the most competitive and promising result when compared to various types of methods. Jayabarathi et al. (2016) proposed a hybrid GWO with Differential Evolution (DE) type mutation and crossover in solving economic dispatch problem which is nonlinear, non-convex and discontinuous in nature with various inequality and equality constraints. The GWO optimiser was being hybridised so that the mutation and crossover were able to be performed. The result has shown that the GWO was able to achieve the objective of the study. Kamboj et al. (2016) used the GWO to find solution to the dynamic economic load of dispatch (ELD) problem and solution for nonconvex of electric power system. The results were then compared to PSO, GA, Biography based optimisation (BBO) and Differential Evolution algorithm (DE). It was discovered that the GWO gives better performance. Additionally, the result also revealed that the GWO was able to solve ELD problem with faster convergence rate. In another study, Moradi et al. (2016) tested the GWO to solve nonconvex of the economic dispatch by the transmission loss and the loading effect of the valve point is also being considered. It was found that the GWO in economic dispatch appeared to be the most efficient solution in solving the big scale of the dispatch problem.

3.2 Power system

Previous study on power system field problems, Mahdad and Srairi (2015) tried to hybridise GWO with pattern search (PS) algorithm in order to prevent power practical against blackout from happening. This is due to the apparition of faults generating units or important transmission lines. During the search process, the target dynamically interacts while best solutions were exchanged between the GWO and PS at some stages. The result indicated that the GWO performed efficiently under critical conditions. Mohamed et al. (2015), used hybrid GWO and ANN to improve the damping powers system oscillations and enhance its stability. The GWO was applied to the ANN in order to find the optimum weight connection and biases which lead to minimising errors. The modified method not only obtained the least error but also fast convergence rate when compared to the original method. Mallick and Nahak (2016a, b) wanted to optimise the damping controller parameters of power flow controller for power oscillation damping. The result showed that the proposed algorithm achieved the objective of the study and also being compared with PSO. Sultana et al. (2016) studied and used GWO to minimize some reactive power losses to enhance the voltage profile of distribution system without violating the system constraints. The GWO was compared with Gravitational Search Algorithm (GSA) and Bat Algorithm (BA). It was found that the GWO gave satisfactory performance as compared to the others. Here, the GWO presented the effective method for power losses reduction, gave voltage enhancements and load ability improvements. Gupta and Saxena (2016) searched parameters for automatic generation control (AGC) of primary governor loop by two interconnected power system areas. This method was then differentiated between GSA, PSO and GA. The GWO outperformed standard deviations in parameters value and the objective functions. Nahak and Mallick (2017) used the GWO to optimize dual unified power flow controller (UPFC) model for damping power oscillations system. The results were observed from various aspects including undershoot, overshoot, time and deviation speed which is lowering the frequency of the oscillations and will eventually enhance the stability to a large extent.

3.3 Classification/gene selection/clustering

In classification or gene selection, the hybrid of the GWO with decision tree to solve gene selection problem in cancer classification of gene expression data has contributed fruitful results. The GWO structure is being merged with a decision tree to figure out the attribute selection in gene expression data. The problem was solved and the GWO clearly gives great results when compared to PSO-decision tree, Support Vector Machine (SVM), decision tree, Self-Organising Map (SOM) and Back Propagation ANN (BPANN) (Vosooghifard and Ebrahimpour 2015). Mirjalili (2015), made an integration method for the GWO with the help of the Multi-Layer Perceptron (MLP) to find the highest classification, approximation or prediction accuracy in training and testing samples. In the meantime, the testing and training samples were trained by the GWO algorithm and the result shows that local optima avoidance is improved. The accuracy of the classification and prediction showed a high result. In addition, Dzung et al. (2015) have made elimination for the high order of the harmonics in maintaining voltage by swapping the angles of the cascaded multilevel inverter by the GWO. The GWO gave a solution in order to obtain selected values to compare it with online method. Saremi et al. (2015) made elimination for poor individuals from the GWO by using the Evolutionary population dynamics (EPD) and also improving the median fitness. The role of the GWO to reinitiate the worst search agents so that the EPD can give exploration for the whole structure. At the end, the performance of the GWO in convergence rate, exploitation, exploration and local optima avoidance is improved and the GWO-EPD was outperformed when being compared with basic GWO.

Zhang and Zhou (2015) proposed to improve the GWO with Powell local optimisation method in solving clustering problems. The Powell's structure is known for its powerful local optimisation ability and is used to embed to GWO as one of the local search operators. Since this study is proposing a new improvement, the tested result was compared to well-known benchmarks and it shows that the proposed method gives outstanding performance thus lead to future works by the researchers. Katarya and Verma (2016) proposed recommender system to contribute significant aspect for filtering information and knowledge management system. Here, they proposed a hybrid of the GWO and fuzzy c-means (FCM), where the GWO results are obtained and then being adapted by FCM. Then, the hybrid method is being compared with K-means, Principal Component Analysis (PCA)-K-means, PCA, PCA-Self Organizing Map (PCA-SOM), SOM-cluster and the hybrid method gave an outstanding performance which shows an efficiency of the performance. Chandra et al. (2016) proposed a modified GWO in order to select the optimum set of services from web services according to Quality of Services (QoS). Here, Genetic Algorithm (GA) crossover is integrated with the GWO and cover the drawback of the GWO on multi-local optima. The result showed that the proposed algorithm is effective and powerful to extract the optimum services and even being compared with basic GWO and GA.

Hybrid of GWO with kernel-based exponential (KEGWO) in developing faster centroid prediction data clustering was proposed by Jadhav and Gomathi (2016). The GWO algorithm was being modified by the exponential function to ensure the wolf positions and the new objective function was derived to calculate the locations by using logarithmic kernel function and the distance difference between two top clusters. In a comparative study, GWO was compared with basic GWO, particle swarm clustering (PSC) and Modified PSC and the GWO showed outstanding results by giving the F-measures of 91.33%. Elhariri et al. (2016) proposed GWO hybridized with Support Vector Machine (SVM) to solve Electromyography (EMG) signal classification with optimum feature subset selection. The GWO combined with SVM to improve the accuracy on one-against-one multiclass SVM. The GWO is designed to optimize feature subset based on RBF kernel and lastly, the accuracy on SVM was used to update the strategy on the GWO. The result was compared with Dragonfly algorithm (DA)-SVM and it shows GWO-SVM gave significant accuracy with 93.22% of the total extracted features.

Elhariri et al. (2016) proposed another GWO-SVM to classify in removing the background, resizing the size and extracting the color elements for every image. The optimum result is obtained by the GWO first and then the optimum result is used by SVM parameters of every testing datasets. In the end, the result shows that the proposed method gave better performance compared to the basic classification of SVM with the accuracy of 92% for RBF and a linear kernel function. Sayed and Hassanien (2015) proposed a hybridization of the fast fuzzy C-means (FFCM) with GWO to remove the interphase cells and extract the chromosome image. In the structure of the algorithm, clustering was made by FFCM and the post-processing of feature selection was made by GWO. The result shows that the proposed method gives 94% accuracy. Emary et al. (2016) proposed a binary GWO to select optimum feature subset of the classification and maximise the accuracy. The individual steps start with binarisation of the best three solutions and then crossover is performed. For the capability of the GWO, for the binary version, it showed better performance since the feature selected was of the best features.

3.4 Proportional–integral (PI) controller

In the fields of proportional plus integral plus derivative (PID) controller, Gupta et al. (2015a, b) investigated optimisation strategy for scaling factors for a fuzzy proportional–integral controller (FPIC) by tuning the FPIC for step set-point and reactor of temperature trajectory tracking in jacketed continuous stirred tank reactor (CSTR). The GWO performance was compared with Backtracking Search Algorithm (BSA), Differential Evolution (DE) and Bat Algorithm and shown excellent result among the comparison methods. Sharma and Saikia (2015) studied the optimisation for proportional plus integral plus derivative (PID) controller in automatic generation control (AGC) for thermal power system plant (STPP). The GWO was able to give an excellent result in optimizing the PID controller by peak overshoot, magnitude oscillation and setting time with or without STTP. The parameters are stable and changes are not large as it does not have to be reset. Li and Wang (2015) make changes for dynamic steam condenser fine-tuning parameter in PI controller. The GWO was compared with GA, PSO and Ziegeler-Nichols (ZN) (DESCRIBE) engineering method. The result showed that the GWO has better performance as compared to the other algorithms.

Mallick et al. (2016) used the GWO to optimize the weight parameter in Automatic Generation Control (AGC) of discontinuous three different thermal systems in PID controller. The result shows that the GWO has achieved the goal of the study to optimize the weight of the parameter by using nine different types of parameter weights. Yadav et al. (2016a, b) used the GWO to tune the parameter of the PID controller to control the liquid level in the Spherical Tank System (STS). The results stated that the GWO has the ability to outperform when tuning the parameters which gives effective result by fulfilling the requirements of the design. Das et al. (2015) used the GWO to optimize the performance of the PID controller used by DC motor for speed control. The GWO results are compared between Ziegler–Nichols rule (ZN), PSO and ABC and it was revealed that the GWO outperformed the other in optimizing the PID controller of DC motor by giving the best set of transient responses.

Yadav et al. (2016a, b) investigated a way to improve the system performance of the parameter in PID controller. As the result, the GWO algorithm makes convergences near to the optimum solution and improved some characteristics of the PID controller. Sundaram et al. (2016) also used the GWO to maintain speed regulation of the induction motor and the PI controller is very poor at many points of the drive. Here, the GWO works efficiently with the response of tuned controller compared to the traditional PI controller. Yadav et al. (2016a, b) optimized PID controller to control the ball position of the magnetic levitation system (MLS) by the GWO algorithm. The result shows that the GWO tuning on the parameter while minimising the performance of the index system. The time and domain for the frequency were improved. Ramadan (2017) used the GWO to search optimum conventional PI controller and Fractional Order (FOPI) of the connected system. By comparing the ABC, Mine Blast Algorithm (MBA) and Whale algorithm (WOA), the GWO was considered the best solution. Yang et al. (2017) searched the interactive optimum PI controller parameter for doubly-fed induction generator (DFIG) based wind turbine by Grouped GWO (GGWO). An adjustment was made on the existed GWO by expanding the hierarchy group of the pack into two independent groups so that the grouping mechanism can be broadened. The works of the GGWO made this method functioning twice as better compared to the basic GWO. As the results, the GGWO was able to extract and achieve optimum wind energy. Then, Precup et al. (2017a, b) proposed an optimisation of discrete-time objective function of Takagi–Sugeno PI fuzzy controllers (T–S PI-FC). The comparison has been made between GWO, PSO and GSA. The performance was evaluated by using the performance value of c_s and a_r. The GWO outperformed others for value c_s while the PSO outperformed others for value a_s while the overall performances are close to each other. Precup et al. (2017a, b) also proposed the GWO as the based tuning for fuzzy control system to reduce parametric sensitivity functions of the sensitivity models. Here, the result shown that the reduction of the number of inputs make the process is a cost effective and made it beneficial to the servo system in mechatronics applications.

3.5 Forecasting natural resources

From the forecasting field, Mustaffa et al. (2015a) made a gold price forecasting from the same method to aim a low error rate with more comparison result from Ant Bee Colony–Least Square Support Vector Machines (ABC–LSSVM) and Cross Validation-LSSVM (CV-LSSVM). It turned out that GWO-LSSVM outperformed the other forecasting methods. Next, Yusof and Mustaffa (2015) investigated the use of the GWO in minimising the error between the forecast and the exact price of the energy commodity for short-term series for crude oil and price of gasoline. As the result, the GWO was compared between Ant Bee Colony (ABC) and the GWO gave outstanding result by producing better forecasting results for gasoline and crude oil. Mustaffa et al. (2015b) applied GWO hybrid with LSSVM to optimize time series forecasting. The parameter was tuned to gain better parameter tuning of LSSVM hyper parameters. Comparison of the end result of basic GWO and other hybrid method showed that the proposed method gives positive feedback. Niu et al. (2016) proposed a hybrid of the GWO and Support Vector Regression (SVR) to decompose and ensemble model for $PM_{2.5}$ (model) forecasting in Harbin and Chongqing, China. Basically, the GWO was used to optimize the parameters of SVR. The proposed method can give better performance in marking different environment and able to enhance the prediction accuracy for $PM_{2.5}$ data. Biyanto et al. (2016) used the GWO to search optimum value of energy consumption of energy sources and raw materials. The GWO gave better performance in terms of global value and speed. Besides, Zainal and Mustaffa (2016) forecasted the future of gold prices which will help minimize the risk of the investments by the GWO. The GWO performed well in predicting feature selection of chosen gold price.

3.6 Image

In the image field, Chaman-Motlagh (2015), made a photonic crystal (PhC) filters design and formulate the design problem as the optimisation problem. With the use of the GWO, it showed that the GWO is able to produce high performance designs and capable to facilitate the design process of the PhC filters. For full optimizer framework (IMoMIR framework) in designing photonic crystal waveguide (PCW) by Mirjalili and Mirjalili (2015), the three main problem surfaces are group velocity, bandwidth and group index. The proposed method was able to design the variety of formation of the PCWs structures. The image enhancement in deducing a technique for automated image enhancements was made by the help of the GWO has been investigated by Murali and Jayabarathi (2016). It is confirmed that the GWO is superior compared to other methods for image enhancing problem.

Li et al. (2016) suggested modification be done to the GWO by Fuzzy Modified discrete GWO. Here, fuzzy Kapur's entropy as the optimum objective function needs modification in order to conduct fuzzy membership so that multilevel image thresholding problem can be solved. The GWO works as usual to solve continuous variables and threshold and the GWO will discretise the threshold. The proposed method improves stability and makes sure the objective function is high. Zhang and Zhou (2017) made optimisation by hybridizing the GWO with Lion algorithm while the LI-GWO made the searching task and need to calculate fitness for every situation and places. Also, the proposed method gave better performance by showing accuracy of lateral inhibition of image preprocessing. Sujatha and Punithavathani (2018) proposed genetic GWO using a combination of images from several sensors which may lower the number of input image data. GGWO was compared with GA and PCA. The GWO gave better visual quality for performances and achievements. Li et al. (2017) made a modified discrete GWO (MDGWO) to improve the optimum solution of search agents by using the weights of the image segmentation. The structure under Kapur's entropy to obtain threshold and result shows that efficiency and fix thresholds are able to be reached which resemble an in-depth research.

3.7 Flow shop

Komaki and Kayvanfar (2015) used the GWO to investigate the time minimization on the two stages assembly flow shop schedule problem on the previous processed job and the result showed better performance when compared with other small sets problems. El-Fergany and Hasanien (2015) studied the hybridization of the GWO and Differential Evolutionary algorithm in solving the optimum power flow problems. According to the changes in the structure, both algorithms used to work out single optimisation problem but at this time, the DE algorithm is being utilised to solve multiobjective problems. The results showed the performance of both algorithms is excelling for solving single objective function strategy.

3.8 Prediction

In the area of prediction and estimation, Gupta et al. (2015a, b) studied the estimation parameters of the Proportional Integral controller (PI) in the area of power system. In order to minimise the area control error, the optimisation method from the GWO was used. It was found out that the GWO gave better performance with different contingencies, step disturbances and load changes as compared to GA, Gravitational Search Algorithm (GSA) and

PSO. Dudani and Chudasama (2016) proposed an Adaptive GWO to search optimum location of Partial Discharge (PD) source locations. Some sensors based on emission techniques have been applied for PD detection. The adaptive techniques included in the structure were parameter dependency, step size or position towards an optimum solution in order to achieve local minimum avoidance and fast convergence. The result shows that the PD source gives ease of use and gives outstanding performance when compared with basic GWO, GA, PSO, linear PSO and Simulated Annealing (SA). Having known the importance of optimisation from Least Square SVM (LSSVM), Mustaffa et al. (2015a, b) made an effort to search for a proficient optimisation technique. The GWO optimised the parameter of interest from the LSSVM. When the training and testing sets are being verified by the LSSVM algorithm, it will then be integrated with the GWO. For comparison of the results, the GWO-LSSVM was able to make a low error rate as compared to the ABC–LSSVM and the GWO.

Jayapriya and Arock (2015), proposed parallel GWO for aligning sequences tradeoff. This happens between accuracy of the solution and lowering computational time for solving multiple alignment sequences. As a result, the estimated solution time was obtained and was compared to CPU parallel approaches time. Kalkhambkar et al. (2016) used the GWO to find optimum size and positions of energy storage and renewable distributed generation (DG). The GWO obtained the optimum positions methodology and made outstanding performance when compared with GA, PSO, Firefly, Symbiotic organisms search (SOS). Zhang et al. (2016) studied and used the GWO to solve unmanned combat aerial vehicle (UCAV) two-dimension path planning problems. The UCAV is able to find safe path while avoiding threats and lowering minimum fuel. The GWO was compared with other metaheuristic methods and the GWO gave better performance as compared to others. Since the GWO has a high level of local optima avoidance, the effort to find a proper prediction of optimum weight sum can be enhanced. Ali et al. (2016) made the GWO identify and developed an estimation model for polymer electrolyte membrane fuel cell (PEFMC). The model was successfully built by the GWO and it showed the reliability, accuracy and effectiveness in matching mathematical and experimental result.

Korayem et al. (2015) proposed to make a hybrid of the GWO and K-means to solve vehicle routing problem cost or distance traveled by the vehicles. Here, K-means plays big roles in assigning the points to k clusters based on the centroids. The centroids will randomly select and reallocate the locations until it stops at a certain point. Wolf from GWO represents the solution and each wolf holds a centroid which corresponds to K clusters. Every centroid is a D dimensional vector. The result showed that the proposed algorithm can achieve optimum and excellent solution according to the benchmark problems. Kamboj et al. (2016) proposed a hybrid of the GWO and PSO to solve single area unit commitment problem by the help of PSO. The PSO will work as the first position of the swarm, then it will be updated using the NPSO and it will then be continuously updated by the GWO. The result showed that the PSO-GWO gives better generation cost than the basic PSO.

Hadidian-Moghaddam et al. (2016) used the GWO to reduce the total annual cost (TAC) of the hybrid system and to solve the sizing of the hybrid of the wind system. The result showed that the GWO was able to find the optimum sizing of the wind system by reducing the cost and fast convergence. Also, the system reliability was improved with improvements made on the inverter efficiency and at the same time, the TAC is decreased. Fouad et al. (2015) used the GWO to find the optimum location for the sink nodes within topology control protocol. The GWO succeeded in reducing the complexity of the time and cost for the energy in constructing the topology. Kaveh and Shokohi (2016) used the GWO to find optimum design for castellated beams. The GWO was found to be one of the potential alternatives of the castellated beam problems and is good in terms of cost compared to the cellular beam.

Khalili and Babamir (2017) made a Pareto GWO to search an arrangement by minimizing the completion time and costs and maximizing the resource of throughput. The study found out that the proposed method was able to achieve better performance according to the time, cost and throughput.

Fathy and Abdelaziz (2017) used full GWO to determine the optimum size and locations of a distributed network in order to minimize the total annual cost. In the end, the product showed that the locations were obtained easily because of the efficiency and ease in solving optimisation problem. Hameed et al. (2016) made a GWO into reducing time and cost for the design process of a crane. The GWO showed a competitive result when compared with PSO, GA and SA. Mohamed et al. (2016) suggested Multiobjective GWO (MOGWO) to optimize two conflict objectives; which are pollution caused by power plants and fuel cost. The structure of the algorithm was first searched for a non-dominated solution and gained the best solution. MOGWO was compared with ABC, PSO and GA and showed a good result in solving multiobjective problems. Mustaffa et al. (2016) proposed the Least Square SVM (LSSVM-GWO) to supply the electricity with minimum cost and reliable load forecasting. Here, the GWO works as optimisation tool for hyperparameters for the LSSVM. Then, the LSSVM-GWO was compared with DE-LSSVM, ABC–LSSVM and FA-LSSVM which the proposed method gave better performance and able to optimize the hyperparameters and gave excellent estimation comparison.

3.9 Parameter tuning

Khalilpourazari and Khalilpourazary (2016) proposed a hybrid of the GWO with the help of Taguchi method to optimise multipass milling process. Here, the main parameter of the GWO is being tuned by Taguchi method to gain the best solution and without trapping local minima. The array in Taguchi method is being used to find the optimum level of the parameter in the GWO. The results showed that the proposed method is able to find feasible solutions for all cutting strategies. Karnavas and Chasiotis (2016) used GWO to estimate unknown permanent magnet of parameters for dc coreless motor. Then the results from GWO and GA were compared, and it showed that the GWO gave outstanding result in giving average prediction error of motor unknown parameters. Precup et al. (2016) used the GWO to tune the parameters from Takagi–Sueno proportional integral fuzzy controller for nonlinear servo system. The GWO gave improvements of the weighted parameter values. This method shows understandable scalar operators. Eswaramoorthy et al. (2016) suggested that the SVM hybrid and the GWO to tune the SVM classifier using the GWO to implement complex classified and nonlinear biomedical signals. The collected data followed by the SVM classifier and the GWO will tune the classifier parameters. The result indicated that the number of errors were slowed down and decreased the risk in human perceptions. Verma et al. (2017) used the GWO to optimize the parameter for fractional order controller and integer order controller. The result obtained shows that the GWO achieved good tuning which minimises the time setting and maintains desired phases of classical problems.

3.10 Welding schedule

Lu et al. (2016) proposed multiobjective discrete GWO (MODGWO) to solve method for real-world scheduling case from the welding process. The steps improvements include decode and encode scheme, initiate social hierarchy, search preys and reduction machine load strategy.

The MODGWO was compared with the NSGA-II and SPEA2, and the MODGWO showed better performance. Hence, this made the MODGWO a verified method since of the case study used replicates a real-world problem. Lu et al. (2017) proposed hybrid multiobjective GWO (HMGWO) to minimize the makespan, instability and machine loads of welding schedule problem. The algorithm worked by encoding and decoding the social hierarchy with the help of grey wolf search and genetic operator. The HMGWO made an outstanding coverage, spread and convergence of real problem welding scheduling.

3.11 Others

The GWO was applied to determine the optimum base station locations for LTE cell planning by Ghazzai et al. (2014). The study wanted to eliminate every redundant base in subareas so that only the safest network locations can be obtained. In the end, the GWO become the most outperformed method when the result was being compared with Particle Swarm Optimisation (PSO). Another study was done by Gupta et al. (2015a, b). The study developed a hybrid of GWO with simulated annealing (SA) to solve time problem in traveling tournament. Here, the GWO works to improve the initial schedules at local optima of the GWO structure and then the SA refined the structure. The result was compared with Ant Colony Optimisation (ACO), PSO, Modified Biogeography-based Optimisation–Simulated Annealing (MBBO/SA) and Biogeography-based Optimisation (BBO/SA) and it was found that the GWO outperformed other methods for this problem.

A study by Song et al. (2015) examined the optimum solution for surface wave dispersion in inversion scheme. As the result, the GWO was able to show balance exploitation and exploration for local optima and the fast convergence happens simultaneously. The result is being compared with Genetic Algorithm (GA) and hybrid algorithm (PSOGSA) and it was found that the GWO outperformed the others. Mitić et al. (2016) investigated to ensure a robot can learn from human by observation and demonstrations by hybridising the GWO with a chaotic bioinspired algorithm. The features from the chaotic algorithm which is one-dimensional chaotic maps are replaced with Gaussian random value in exploration parameter of the GWO. At the end, the robot successfully made uncertain and unavoidable commands based on the influence from the demonstrator. Yao et al. (2016) proposed a new GWO known as Improved GWO (IGWO) to plan optimum trajectories of the multi-unmanned aerial vehicle (UAV) for target tracking in an urban environment. The IGWO utilized the Model Predictive Control (MPC) in terms of searching ability, stability and computation efficiency. In the end, the target tracking problem was solved by the IGWO. Karnavas et al. (2016) used the GWO to minimize the machine total losses and wanted to make the efficiency to the max of inner rotor design problem. The GWO then compared with GA and PSO and the GWO successfully implemented the design problem and gave competitive alternative design in replacing traditional induction motor. Sultana et al. (2017) used the GWO to reduce active and reactive energy losses in distributed generation (DG). The GWO shows a reliable performance besides being simple and competent to handle for solving DG allocations problems.

The application of the GWO that has been extensively reviewed above is presented and summarized in Table 1 below.

Table 1 Previous study of the GWO

No.	Author	Proposed algorithm	Application	General performances	Results
1.	Wong et al. (2014)	GWO	Economic dispatch problem of power system	GWO > CS, Firefly, ABCNN, ABC, BBO, LI, HM, QP, GAMS	Very competitive results in terms of minimizing total fuel cost and lower transmission loss
2.	Ghazzai et al. (2014)	GWO	LTE cell planning for multiple user in subareas	PSO > GWO	Eliminates eventual redundant base stations to keep the minimum number of base stations required to ensure a safe network operation
3.	Vosooghifard and Ebrahimpour (2015)	Hybrid GWO	Gene selection in cancer classification	HGWO > PSO-decision tree, SVM, decision tree, SOM, BPANN	Proposed method achieved better performance in comparison with other methods
4.	Gupta et al. (2015a, b)	GWO	Tune the scaling factors of the fuzzy proportional–integral controller (FPIC)	GWO > BSA, DE, BA	GWO outperformed other methods
5.	Gupta et al. (2015a, b)	Hybrid GWO and simulated annealing	Travelling tournament problem	HGWO > MBBO/SA, ACO, PSO, BBO/SA	GWO achieves local optima in very less time
6.	Mustaffa et al. (2015a, b)	Hybrid GWO-LSSVM	Time series forecasting	HGWO-LSSVM > ABC–LSSVM, GWO	Produce lower error rates as compared
7.	Mustaffa et al. (2015a, b)	Hybrid GWO-LSSVM	Gold price forecasting	GWO-LSSVM > ABC–LSSVM, CV-LSSVM	Produce lower forecasting error
8.	Chaman-Motlagh (2015)	GWO	Designing photonic crystal (phc) filters	N/A	The proposed method is able to be extended and applied to any kind of optical filters
9.	Mohamed et al. (2015)	Hybrid GWO-ANN	Damping of power systems oscillations and enhancement the power systems stability	N/A	Reach to smaller error value with faster convergence and has better performance than the traditional PI controller
10.	Mirjalili and Mirjalili (2015)	Multiobjective GWO (MOGWO)	Framework (IMOMIR framework) for designing photonic crystal waveguide (PCW)	N/A	Proposed framework is able to design the various forms of PCW structures reliably

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
11.	Song et al. (2015)	GWO	Surface wave dispersion curve inversion scheme	GWO > GA, PSOGSA	A good balance between exploration and exploitation that results in high local optima avoidance and a very fast convergence simultaneously
12.	Mirjalili (2015)	GWO-MLP trainer	Highest classification, approximation, or prediction accuracy for both training and testing samples	N/A	Improved local optima avoidance and high level of accuracy in classification and approximation of the proposed trainer
13.	Dzung et al. (2015)	GWO	Switching angles for a cascaded multilevel inverter	N/A	GWO also gives solutions to eliminate some high order harmonics while maintaining the required fundamental voltage
14.	Saremi et al. (2015)	GWO-EPD	Evolutionary population dynamics (EPD) deal with the removal of poor individuals in nature	GWO-EPD > GWO	Improve the performance of the GWO algorithm in terms of exploration, local optima avoidance, exploitation, local search, and convergence rate
15.	Sulaiman et al. (2015a, b)	GWO	Power dispatch in nonlinear optimization problem in power system	N/A	Best combination of control variables and the less voltage deviation minimizations can be achieved
16.	Mahdad and Srairi (2015)	Hybrid GWO-patter search algorithm	Power system against blackout	N/A	Prove the efficiency of the proposed planning strategy using hybrid method to ensure system security under critical situations
17.	Sharma and Saikia (2015)	GWO	Optimization of secondary controller gains for first time in Automatic generation control (AGC))	N/A	GWO optimized PID controller's performance is better than others in terms of settling time, peak overshoot and magnitude of oscillations in the system with or without STPP

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
18.	Komaki and Kayvanfar (2015)	GWO	Find the jobs sequence such that completion time of the last processed job is minimized	N/A	Comparing GWO to other well-known algorithms revealed that GWO has better performance
19.	El-Fergany and Hasanien (2015)	Hybrid GWO-DEA	Optimum power flow (OPF) problem	N/A	Results have proven the high performance of both algorithms for solving the single objective function strategy
20.	Yusof and Mustaffa (2015)	GWO	Short-term time series forecasting for crude oil and gasoline price	GWO > ABC, DE	GWO model outperformed DE in both crude oil and gasoline price forecasting. GWO produces a better forecast for gasoline price as compared to the ABC model
21.	Mustaffa et al. (2015a, b)	Hybrid GWO-LSSVM	Free hyperparameters of LSSVM in order to achieve good generalization for the gold price	GWO-LSSVM > GA-LSSVM, ABC–LSSVM, GWO	GWO-LSSVM possess lower prediction error rate
22.	Gupta and Saxena (2015)	GWO	Proportional Integral Controller (PI) for Automatic Generation Control (AGC) of two area power system	GWO > GA, GSA, PSO	Better damping performance is exhibited by GWO under different contingencies, load changes and step disturbances in both areas
23.	Zhang and Zhou (2015)	Powell GWO (PGWO). Improved GWO	Improves the original GWO in solving complex optimization problems Clustering	N/A	Data clustering demonstrate the superior performance of PGWO algorithm
24.	Li and Wang (2015)	GWO	Fine-tuning of PI controller parameters	GWO > GA, PSO, ZN method	GWO algorithm has better control performance
25.	Sulaiman et al. (2015a, b)	GWO	Economic Dispatch (ED) problem to obtain the combination of the fuel based power generation so that the minimum cost can be achieved	N/A	GWO offers promising and competitive results compared to other methods presented in this paper

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
26.	Korayem et al. (2015)	Hybrid K-means-GWO	To minimize the total cost or distance travelled	N/A	GWO obtain optimum and near-optimum solutions for benchmark problems
27.	Jayapriya and Arock (2015)	parallel GWO (sequences)	For solving multiple sequence alignment, an NP complete problem	N/A	Proposed technique yields an approximate solution in less time than CPU parallel approaches
28.	Dudani and Chudasama (2016)	Adaptive GWO (AGWO)	Location of Partial Discharge (PD) source location	AGWO > GWO, GA, QGA, PSO, Linear PSO, SA	The AGWO result of various unconstrained problems proves that it is also an effective method for solving challenging problems with unknown search space
29.	Katarya and Verma (2016)	Hybrid GWO-FCM	Predicts rating of a movie for a particular user based on his historical data and similarity of users	GWO-FCM > K-means, PCA-K-means, PCA, PCA-SOM, SOM-cluster, FCM, KM-PSO-FCM, GAKM-Cluster	Efficiency and performance are enhanced and also offered better recommendations when compared with previous work
30.	Mitić et al. (2016)	Hybrid Chaotic GWO	Robot learning from human teacher through demonstrations or observations	Comparison of so many sets	The uncertainty in robot commands, unavoidably generated by the influence of the demonstrator, is successfully solved by the LFD-based CGWO algorithm
31.	Mallick et al. (2016)	GWO	Optimize the weighty parameters in automatic generation control(AGC) of interconnected three unequal area thermal system	N/A	It is observed that during high value of SLP proposed controller performed well and also during simultaneous occurrence of SLP

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
32.	Mallick and Nahak (2016a, b)	GWO	Damping controller parameters for a unified power flow controller connected to a single machine infinite bus power system for power oscillation damping	GWO > PSO	GWO based damping controller damps the oscillation as well
33.	Khalilpourazari and Khalilpourazary (2016)	Robust GWO (RGWO) help of robust Taguchi method	Optimize multi-pass milling process, selection of optimum values for the parameters of the process is of great importance	N/A	Outperforms the other solution methods in the literature as well as two novels meta-heuristic algorithms by obtaining better and feasible solutions for all cutting strategies
34.	Chandra et al. (2016)	Modified GWO (MGWO)	Plenty of web services exhibiting similar functionality but different in terms of Quality-of-Service (QoS) requirements	MGWO > GWO, GA	The MGWO is an effective and powerful approach to extract optimum services in diverse situations
35.	Karnavas and Chasiotis (2016)	GWO	The parameters of an unknown permanent magnet dc coreless micro-motor are estimated	GWO > GA	GWO due to its inherent search agents' adaptation rule nature, is faster than GA in estimating the motor unknown parameters
36.	Jadhav and Gomathi (2016)	kernel-based exponential grey wolf optimizer (KEGWO)	Developed for rapid centroid estimation in data clustering	KEGWO > GWO, mPSC, PSC,	Clustering algorithm obtained the maximum F-measure of 91.33%
37.	Kalkhambkar et al. (2016)	GWO	Size and location of energy storage, and renewable DG such that the annual energy losses of the distribution network are minimized	N/A	Significant loss minimization is obtained by the proposed joint optimum allocation methodology when solved with GWO optimization
38.	Yadav et al. (2016a, b)	GWO	The parameters of the PID controller are optimized using GWO	N/A	The GWO algorithm tuned the parameters and fulfilled all the design requirements

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
39.	Jayabarathi et al. (2016)	DE-type mutation and crossover with GWO (Hybrid GWO)	Economic dispatch problems	N/A	The comparisons show that the hybrid grey wolf optimizer used in this paper either matches or outperforms the other methods
40.	Sultana et al. (2016)	GWO	Reactive power losses and improve the voltage profile of the distribution system	GWO > GSA, BA	Presented approach is more effective in terms of loss reduction, voltage profile improvement and load ability enhancement of distribution system
41.	Zhang et al. (2016)	GWO	UCAV two-dimension path planning problem while avoiding the threats areas and costing minimum fuel	GWO > GGSA, FPA, NBA, BSA, ABC, CS	A high level of local optima avoidance, which enhances the probability of finding proper approximations of the optimum weighted sum cost of this path
42.	Lu et al. (2016)	Multi-objective discrete GWO (MODGWO)	Scheduling case from a welding process	MDGWO > NSGA-II, SPEA2	The superiority of the MODGWO is significant by conducting the wilcoxon signed rank test
43.	Elhariri et al. (2016)	GWO-SVM	The feature set dimensional reduction. The proposed classification system has been tested via solving the problem of electromyography (EMG) signal classification with optimum features subset selection	GWO-SVM > DA-SVM	GWO-SVM accuracy of 93.22% using 31% of the total extracted features
44.	Kamboj (2016)	PSO-GWO	Single-area unit commitment problem using novel particle swarm optimization algorithm	N/A	Generation cost of hybrid PSO–GWO is better than classical and novel PSO
45.	Yao et al. (2016)	IGWO	Optimum trajectories of multi-UAVs for target tracking in the urban environment	N/A	The simulation results show the effectiveness of the proposed hybrid method to solve target tracking problem

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
46.	Khamboj et al. (2016)	GWO	A solution of nonconvex and dynamic economic load dispatch problem (ELDP) of electric power system	GWO>PSO, GA, BBO, DE, ANN-EPSO, FEP, CEP, IFEP, MFEP	GWO is able to minimise total fuel cost and lower transmission loss. Also, convergence of GWO is very fast
47.	Elhariri et al. (2016)	GWO-SVM	Classification approach was implemented by applying resizing, remove background, and extracting color components for each image	N/A	Proposed GWO-SVMs approach outperformed the typical SVMs classification algorithm with classification accuracies of 92% for RBF and linear kernel functions
48.	Das et al. (2015)	GWO	Optimize the performance of a PID controller used in DC motor speed control	GWO>(Ziegler–Nichols rule) ZN, PSO, ABC	The optimization of PID Controller in speed control of dc motor using GWO gives the best set of transient response specifications in comparison to other soft computing methods
49.	Yadav et al. (2016a, b)	GWO	Improve the system performance the parameters of the PID controller are optimized using (GWO)	N/A	GWO algorithm converge to a near optimum solution and provides improved characteristics compared to the conventional PID controller
50.	Karnavas et al. (2016)	GWO	The minimization of the machine's total losses and therefore the maximization of its efficiency, the design is conducted by solving an optimization problem	GWO>GA, PSO	GWO provide very competitive alternative designs to replace traditional low-speed induction-motor/gearbox systems
51.	Hadidian-Moghaddam et al. (2016)	GWO	Minimise the total annual cost (TAC) of the hybrid system	N/A	HPWGS reliability characteristics are weakened with decreasing the component availability, and the supply reliability of the HPWGS is improved by increasing the inverter efficiency while the TAC is decreased

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
52.	Moradi et al. (2016)	GWO	Solve the non-convex economic dispatch Problem with transmission loss and valve-point loading effect	N/A	GWO may be applicable for solving non-convex ED problem, regardless of factors such as aggregated system loading, system scale and its configuration
53.	Niu et al. (2016)	GWO-SVR	A decomposition-and-ensemble model is proposed for PM2.5 concentration forecasting. GWO algorithm is proposed for short-term PM2.5 concentration forecasting	N/A	The proposed hybrid has wider applicability and can enhance the prediction accuracy and directional prediction by simplifying the intrinsic complexity
54.	Murali and Jayabarathi (2016)	GWO	Image enhancement is considered to be an optimization problem	N/A	Visual and mathematical results prove the superiority of GWO and PSO over HE
55.	Fouad et al. (2015)	GWO	Find optimum location of the sink node within a topology control protocol	N/A	Efficiently reduced the time complexity and energy cost those required to construct a topology
56.	Sayed and Hassanien (2015)	Hybrid (Fast Fuzzy C-Means –GWO)	Remove interphase cells and extract chromosomes from metaphase chromosomes image	N/A	Good performance of the proposed approach. It obtains overall 94% accuracy
57.	Gupta and Saxena (2016)	GWO	Find the parameters of primary governor loop for successful Automatic Generation Control of two areas' interconnected power system	GWO > GSA, PSO, GA	GWO outperforms all three optimization methods and compared with other algorithms on the basis of standard deviations in the values of parameters and objective functions
58.	Kaveh and Shokohi (2016)	GWO	For optimum design of castellated beams	N/A	GWO is a potential optimization algorithm to solve castellated beam problems. It is better than cellular beam from the point of view of the cost

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
59.	Precup et al. (2016)	GWO	Tune the parameters of Takagi–Sugeno proportional integral fuzzy controller for class nonlinear servo system	N/A	GWO-based tuning approach have been expressed in easily understandable scalar operations against the GWO
60.	Sundaram et al. (2016)	GWO	Maintain speed regulation of induction motor is a major challenge	N/A	Dynamic response of the motor obtained with GWO based tuned controller is more efficient than with the traditional PI controller
61.	Li et al. (2016)	FUZZY Modified discrete GWO	Conduct fuzzy membership initialization	FMDGWO > FGWO, FDE, MDGWO, EMO	FMDGWOA improves the stability while ensures higher objective function value
62.	Yadav et al. (2016a, b)	GWO	Optimized proportional–integral-derivative (PID) controller to control the ball position of the magnetic levitation system (MLS)	N/A	The system performance is improved in terms of time and frequency domain by optimizing the parameters of the PID controller using r GWO
63.	Emary et al. (2016)	Binary GWO	Feature selection domain for finding feature subset maximizing the classification accuracy while minimizing the number of selected features	N/A	Proposed feature selection method proves better separability and converges to same solution regardless of the used randomness
64.	Eswaramoorthy et al. (2016)	GWO	Biomedical signals like intracranial electroencephalogram	N/A	Optimum tuning of classifier parameters lowers errors due to the manual elucidation and decreases the risk in human perceptions and repeated visual diagnosis
65.	Ali et al. (2017)	GWO	Accurateness model for the polymer electrolyte membrane fuel cell (PEMFC), that can precisely mimic and simulate the electrical characteristics of actual PEMFC	N/A	PEMFC model has been developed with accurately identified parameters using the GWO. The data are well-matched with actual experiment with lesser value

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
66.	Khalili and Babamir (2017)	Pareto GWO	Scheduling in the cloud computing environment to minimize completion time of dependent tasks and cost	N/A	Multiobjective algorithm presents a better trade-off between 3 conflicting objectives
67.	Verma et al. (2017)	GWO	Optimise the parameters of fractional order controller for controlling two classes of systems: time-delay and higher-order system	N/A	The GWO technique works efficiently for fine tuning the parameters. GWO conveniently minimizes the setting time and maintain the desired phase margin of the classical control problems
68.	Sultana et al. (2017)	GWO	For optimum placement and sizing of multiple Distributed Generation (DG), aimed at reducing active and reactive energy losses in the distribution system	N/A	Best performance recorded via the proposed GWO method in terms of not only active and reactive energy loss but also voltage profile and convergence characteristics
69.	Nahak and Mallick (2017)	GWO	An optimized dual UPFC controller for damping power system	N/A	Performance of proposed optimised dual controller is much better in damping of low-frequency oscillations
70.	Fathy and Abdelaziz (2017)	GWO	Optimal size and location of ESSS in a distribution network and to minimize the total annual cost of	N/A	The obtained locations and sizes of ESSS encourage the usage of the proposed methodology due to its ease and efficiency
71.	Ramadan (2017)	GWO	Finding the optimum gain scheduling of the conventional Proportional Integral (PI) and the Fractional Order (FOPI	GWO > ABC, CS, MBA, MSA, WOA	The GWO is considered as the best solution for a voltage regulator for both controllers

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
72.	Hameed et al. (2016)	GWO	Attempt to reduce time and cost involved in the design process of crane design	GWO > PSO, GA, SA	GWO algorithm is able to provide very competitive results
73.	Zhang and Zhou (2017)	LI-GWO	For template matching (image)	LI-GWO > LI-BBO, LI-BA, LI-SMS, LI-CA	The proposed method achieves the best balance in comparison to other algorithms based on lateral inhibition in terms of estimation accuracy and the computational cost
74.	Mohamed et al. (2016) (23)	MOGWO	Environmental pollution caused by thermal power plants and fuel cost, were considered for optimization	MOGWO > ABC, MSLFA, PSO, GA	The proposed approach can provide more effective in obtaining solutions in compared with original version and other approaches
75.	Sujatha and Punithavathani (2018)	Genetic GWO	Combine images from several sensors, which leads to the decreased amount of input image data, producing an image with more accurate data	GGWO > GA, PCA	GGWO based proposed method performs better visual quality than other methods
76.	Biyanto et al. (2016)	GWO	Energy consumption in a condenser and re-boilers, based on training process	N/A	GWO has better performance than PSO in terms of speed and global value while reducing energy consumption a half of value before optimization
77.	Zainal and Mustaffa (2016)	GWO	Predict the future prices so that gold can be bought and sold at profitable positions and reduce the risk of investment	N/A	GWO-based time series model with feature selections are chosen to forecast gold price that uses GWO algorithm for parameter estimation
78.	Yang et al. (2017)	GGWO	The optimum interactive PI parameter tuning of DFIG based wind turbine	GGWO > MFO, GWO, PSO, GA	GGWO can extract the largest amount of wind energy and effectively restore the system

Table 1 continued

No.	Author	Proposed algorithm	Application	General performances	Results
79.	Lu et al. (2017)	HMGWO	Minimise the makespan, machine load and instability simultaneously	HMOGWO > NSGA-II, SPEA2, MOGWO	HMOGWO outperforms other algorithms in terms of convergence, spread, and coverage
80.	Li et al. (2017)	MDGWO	Updating mechanism of the search agent by the weights	MDGWO > GWO, MTEMO, DE, ABC	MDGWO can search out the optimum thresholds efficiently and precisely
81.	Mustaffa et al. (2016)	GWO-LSSVM	Supply the electricity with minimal costs, reliable load forecasting is one of the critical issues	LSSVM-GWO > DE-LSSVM, ABC–LSSVM, FA-LSSVM,	GWO is proved to be able to optimize the hyperparameters value of LSSVM and give better prediction on comparison
82.	Precup et al. (2017a, b)	GWO	PI fuzzy controller	GWO > PSO, GSA PSO > GWO, GSA	GWO outperform others for c_s value while PSO outperform for a_r value
83.	Precup et al. (2017a, b)	GWO	PI fuzzy controller with Takagani–Sugeno–Kang	N/A	Reduce inputs make a cost effective for mechatronics application

4 Discussion and future works

From the literature, there are trending patterns occurred from the year 2014 to 2017. Figure 4 shows various type of applications in terms of the total number of studies from each year. The years shown clearly demonstrate that the GWO was applied into different fields such as gene selection, time and gold price forecasting, economic dispatch problem, parameter tuning, cost estimation, filter image, damping power system, flow shop, welding schedules and others. As stated in the figure, 2016 shows the highest use of the GWO compared to other years. This clearly shows that the use of the GWO in the optimisation field has yield interest after 2 years. Also, it can be seen that the variety of application in implementing the GWO in their own problems are inconsistent based on the interest and their ulterior objective that researchers aimed to achieve. Despite the high frequency of application of the GWO in optimising problem, some of the applications were halted for the following years since the problems were already solved. Such was the case in the fields of gene selection, classification, and clustering. Meanwhile, the most frequent use of the GWO for optimisation besides being used in gene classification and clustering was PID controller and cost estimation. On the contrary, the least use of the GWO was welding schedules, prediction, flow shop, damping power system, economic dispatch problem and others. Here, others are grouped as unknown area since the number of uses is at least once per used and it consists of different types of applications such as finding LTE cell planning position, traveling tournament, wave dispersion and robot learning from the human behaviors. In addition, even the numbers of the hybridisation and modification (Rodríguez et al. 2017a, b, c) of the GWO were not stated, the improvements were still growing depending on the problems either to improve current problem that had used the GWO before or completely used for different problems according to their suitability and desired optimisation. The modification and hybridisation of the GWO are increasing every year and still some of the problems are still using the basic GWO given that the fundamentals itself are already solid even before it is being improved or modified. Here, the used of the GWO depended on the problems of the optimisation and the easiness of the use of this method.

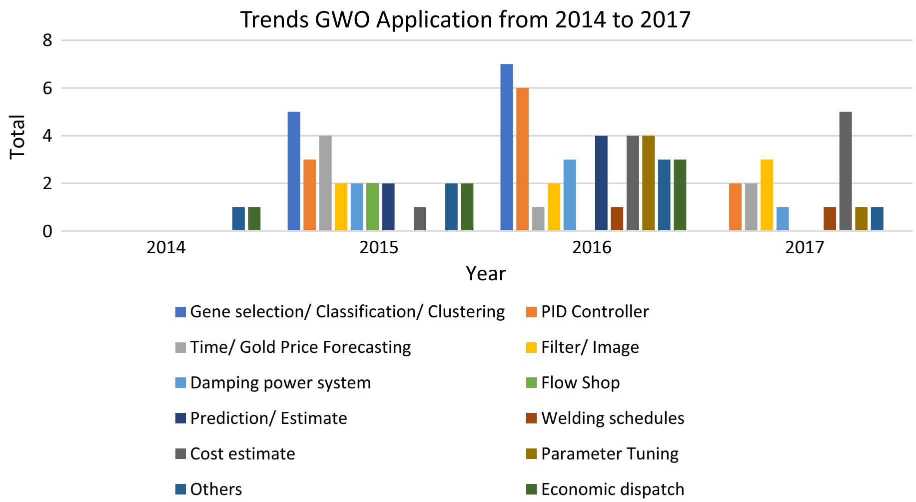

Fig. 4 Trends GWO application from year 2014–2017

From the works done by the previous researchers, it has been proven that the use of the GWO is wide and broad. Optimisation problem varies in every research and the No Free Lunch theorem stated that all problems do not have the same solutions. This leads to the refinement of the optimisation techniques such as the GWO. As reviewed in the previous section, the basic GWO was adjusted into many shapes of changes to fit and fix the desired problems and that is how modification and hybridisation existed. Some of the main structures of the GWO which are tracking, encircling and attacking preys are adjusted and changed according to the objective of the studies. It begins from the initial step in which they changed the wolves' positions by putting a selective value and mathematical method such as probabilistic method (Gupta et al. 2015a, b), changing the wolves as Kcentroids (Korayem et al. 2015), initiliase cluster and position before clustering (Sayed and Hassanien (2015), initializing the wolves as multiple sequence alignment (Jayapriya and Arock 2015) and made changes of the wolves' position as binary string for solving binary problems (Emary et al. 2016). Furthermore, many researchers made changes when the wolves are at the stage of encircling preys to enhance their exploitation and exploration method. Many changes were made since this method involves a big space and there are no limitations of the algorithm on selecting spaces as long as it moves in the stated boundary. The Artificial Neural Network (ANN) trainer such as Multi-Layer perceptron (MLP) used the GWO to lessen the biased on the weight of the trainer so that the search exploration can be enhanced and accelerated (Mirjalili 2015). The Evolutionary Population Dynamics (EPD) removes the poor search of the GWO and reinitailise the search agents (wolves) around search spaces (Saremi et al. 2015). The position of the target was changed based on the information obtained through patterns search technique for a balance searching process (Mahdad and Srairi 2015). In order to execute the emission technique and do the randomization on the search spaces area (Niu et al. 2016), avoidance of the search agents by not sticking to local optima (Dudani and Chudasama 2016) made the searching global so that the points of agents gets bigger (Katarya and Verma 2016). Other than that, the objective function was firstly produced by Khalilpourazari and Khalilpourazary (2016) before implemented to the GWO, and the same method was being applied by Gupta et al. (2015a, b), Mustaffa et al. (2015a, b) when using the Least Square Support Vector Machine (LSSVM) first to obtain the objective function before being executed in the GWO.

Every technique has its own unique characteristic and some minor drawbacks that cannot be overlooked despite the various evolutions and new techniques being introduced. Recent literature has shown that the GWO has the ability to converge and possess better characteristic than other techniques. Not only that, the GWO also has a good balance between the exploitation and exploration, especially for high local optima avoidance in search spaces and mostly the metaheuristic methods are simple, flexible, easy to implement and has a little parameter to tune and this makes it easier to adapt into various type of problems. Moreover, the GWO does not need a bigger storage and has fast convergence due to its continuous reduction of search space and just a little need for decision of variables. For the disadvantages, sometimes, the ability of being dependent to or being limited on some mechanisms behavior and the balance between exploitation and exploration of searching preys made the GWO hard to move without the pack's help. Furthermore, some researchers said that with a little parameter to tune, it will have less control on the algorithm. Not only that, when it comes to handling unimodal problems, the speed will be slower in the end of the process in order to find the optimum solution even though at the beginning it helps to speed up the process. For multimodal problems, because of the GWO behavior, it is reported that the searching can easily stuck at the local optima, stops for the next progress and loses its diversity because of the lack of information sharing among the member in a pack.

Overall, many improvement and adjustments have been made by previous researchers and in short, every different objectives of study need different methods to achieve the desired results. The solution of every problem cannot be limited to just one method and thus the development of the solution will continuously expand. In the future, since the GWO is widely used in rectifying engineering problems, it is recommended that exploration be made in the field of optimisation as shown below:

1. Combination with other traditional optimisation such as Taguchi method, linear programming, integer programming, or dynamic programming for stronger optimisation.
2. Optimisation exploration in various fields such as in medical, sports, geoinformatics, manufacturing engineering and many more.
3. Combination or hybridization with evolutionary algorithm such PSO, GA, or any nature based optimisation such ABC for enhancement of the speed of the performance or other problems.
4. Enhancements with other local search since the GWO is part of a metaheuristic which is well known for its good global optima.

5 Conclusion

In this study, the past researchers in regards of the use of the GWO for solving optimisation in various applications are considered. The structures of the GWO are considered, its advantages and disadvantages are stated and analysed. The good features and drawbacks of the GWO specified based on a few key features of the algorithm and flow based. From the statistical results collected, the GWO is widely used in many fields according to the problem specifications. Based on the results from the experiment, the GWO was able to outperform other techniques such as PSO, GA, ABC, and SA. However, based on the No Free Lunch theorem, it is clearly shown that the performance of the GWO was outperformed by any comparison of the optimisation method. Moreover, there are other problems that cannot be solved by the GWO because of the unavailability of non-traditional or any technique that could be used to solve all optimisation problems. Moreover, the discussion on the properties of the GWO algorithm and how it countered the problems based on various applications such as parameter tuning, economy dispatch problem, cost estimation and gene classification are discussed in details. Based on the findings, the GWO had the ability to solve single and multiobjective problems besides its good local search optima which always gives excellent performance and analysis from numerous fields by the GWO optimisation technique. In addition, the modification of the GWO gives a superior performance either in optimising the problem or the GWO itself. To conclude, since there is still room of improvement, the GWO could be extended into various hybridisations and modifications according to necessity of the problems. Therefore, the results of this study could be used by other prospective researchers to a different process or for improvement purpose by taking into consideration on the uses, advantages and drawbacks of other system proposed by previous researchers.

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