Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268 e-ISSN: 2395-3454	Vol. 16	No. 2	pp. 409-417	2017

Original Research Paper

Open Access

Swarm Based Control Strategies For Air Pollution And Electricity Production By Multiobjective Optimization

Mahmad Raphiyoddin Shaphiyoddin Malik and E. Rasul Mohideen
Department of Civil Engineering, B. S. Abdur Rahman University, Chennai, India

Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 06-06-2016
Accepted: 16-07-2016

Key Words:
Thermal power plant
Swarm intelligence
Grey wolf optimizer
Air pollution

ABSTRACT

Air pollution has drastically increased now-a-days due to rapid urbanization and industrialization. There are many sources of air pollution, but the predominant one is caused by burning of coal in Thermal Power Plant (TPP). The TPPs are the major sources of electricity production, especially in developing countries like India. The non-conventional energy sources like solar or wind will produce pollution-free electricity, unfortunately they are in their infancy, and hence the conventional TPP usage is still encouraged. The installation of new TPPs for pollution free electricity production is nearly impossible, hence optimizing existing TPPs for air pollution reduction and maximizing electricity production is of prime importance. This can be achieved by constructing a mathematical model of TPPs and optimizing the same. There are many mathematical techniques to model optimization of air pollution and power generation. This paper proposes a new mathematical model for TPPs based on multiple objectives to be optimized simultaneously. Further, it integrates multi-objectives with Weighted distance Grey Wolf Optimizer (WdGWO) for minimizing air pollution and maximizing electricity generation of Delhi Thermal Power Plants. The presented results demonstrate the effectiveness of the proposed mathematical model and the algorithm.

INTRODUCTION

Due to rapid industrialization and urbanization, the demand of power generation has become inevitable. Most of the power comes from Thermal Power Plants (TPPs) that accounts for approximately 65% of the world's power supply. The majority of TPPs generate power by burning of fossil fuels. The fossil fuels like coal, petrol, diesel and kerosene etc. are major source of energy due to their high calorific value and their availability in abundance. This burning of fossil fuels in TPPs causes huge amount of air pollution (Basu 2010). The major harmful gases and pollutants released in the air are sulphur dioxide (SO_2), oxides of nitrogen (NOx) and total suspended particulate matter (TSPM). Air pollution has hazardous effect on both environment and human health, hence is a serious concern of the century (Le et al. 1995). Though there are many ways to reduce and/or to avoid the generation of poisonous gases with the usage of non-conventional energy sources (solar, wind etc.), but they are still in their infancy and almost non-feasible for the huge demand of the society.

Since the construction of new, efficient TPPs is also relatively reduced or infeasible, hence efficiency improvement of existing TPPs is on the radar of the government and researchers. This can be achieved by constructing mathematical model of air pollution and electricity generation for optimal strategies. There are many mathematical models available to reduce air pollution and increase the power generation in existing TPPs (Rajesh et al. 2015). However, existing mathematical models involves single objective with certain constraints. These models, though fit to the near reality, but still do not give the required strategies. This paper proposes a new mathematical model consisting of multiple objectives to simultaneously maximize electricity generation and reduce the air pollution.

However, to optimize these mathematical models, the optimizing algorithms are required as an essential tool. These equivalent models have complex characteristics and involve multiple objectives. Due to the complexity involved in optimization most of the classical optimization methods fail to give required solution (Fletcher 2000, Bonnans & Sagastizabal 2003, Vanderbei 2008) and hence an alternative like Swarm Intelligence (SI) may be preferred. The SI algorithms are the optimizing paradigms developed by mimicking the searching behaviour from nature and used for solving complex optimization problems (Eberhart & Kennedy 1995b, Eberhart & Kennedy 1995a, Karaboga 2005, Karaboga & Basturk 2006, Yang & Suash 2009, Yang 2009, Civicioglu 2013). They have proved well on standard benchmark optimization problems. Further this paper integrates multiple objectives with Weighted distance Grey Wolf Optimizer (WdGWO) for minimizing air pollution and maximizing electricity generation of Delhi TPPs. The following sections of the paper briefly explain about the power generation and air pollution, problem formulation and pollution statistics, Swarm Intelligence and Weighted distance Grey Wolf Optimizer.

POWER GENERATION AND AIR POLLUTION

The rapid growth in industrialization and urbanization has made sustained power requirement an essential component of the present day society. The majority of the power comes from Thermal Power Plants (TPPs), and it accounts for 60% to 70% in the world. The process of power generation in the TPPs is by rotating turbines and alternators at a relatively high speed. This rotation is made possible with the generation of high pressure in the boilers by burning fossil fuels. The majority of the fossil fuels are coal, petrol, diesel and kerosene etc. The coal is preferred as major fossil fuel in most of the TPPs as it is available in abundance and is cost effective. The burning of coal produces very high thermal energy as it has high calorific value. This burning of coal causes air pollution, in addition the poisonous gases like sulphur dioxide (SO_2), oxides of nitrogen (NOx) and total suspended particulate matter (TSPM) are also produced as a byproduct. The SO_2 is a qualitative air pollutant and is injurious to human health. Its major sources are combustion of coal and oil, rubber vulcanization plants and chemical industries (Rajesh et al. 2015). The NOx is produced by burning of coal, gas, oil, gasoline, etc. at very high temperatures (Rajesh et al. 2015). The TSPM is a complex multi-phase system in the air consisting of particle sizes ranging from 0.01 m to 100 m (Devi et al. 2007, Wan-Kuen & Joon-Yoeb 2006, Rajesh et al. 2015). It is difficult to stop the operation of existing TPPs, as the non-conventional energy sources like solar and wind are not efficient enough to provide sufficient amount of electricity for the present demand. The non-conventional energy sources are still in their infancy, especially in developing countries like India. Hence there is a requirement of finding a sustainable solution which increases electricity production and reduce the increasing pollutants. In this paper authors have proposed multi-objective optimization model which may be helpful to reduce the rising quantity of pollutants from TPPs as well as help to maintain electricity production. The following section provides the details of TPPs of Delhi (India) and presents an optimizing model.

PROBLEM FORMULATION AND DATA

This section provides the details of multiobjective optimization, problem formulation of TPP and related data of Delhi TPP.

Multiobjective optimization: A multiobjective optimization problem (MOP) either minimizes or maximizes more than one objective simultaneously.

$$[f_1(x), f_2(x), f_3(x), \ldots, f_k(x)]$$

Where x is an n-dimensional decision vector and k is the number of objectives.

Multiobjective optimization problem involves solving a set of conflicting objectives simultaneously. Hence, there can be a set of optimal solutions to the given problem. The tradeoffs amongst them are defined in terms of Pareto optimality (Huang et al. 2006, Knowles 2006). The Pareto optimality may be defined as follows: a decision vector x is said to be Pareto optimal with respect to search space if there is no other decision vector that is better than x in the search space. The set of all Pareto optimal solutions in the decision space is termed as Pareto optimal set and the corresponding set of objective vector is termed as Pareto optimal front. The aim of multiobjective optimization algorithm is to obtain Pareto optimal front accurately.

Delhi thermal power plant problem formulation: The following problems are built from Delhi TPPs statistics:

Maximize Electricity

$$f_1(\vec{X}) = 135X_1 + 1500X_2 + 135X_3 + 705X_4 + 350X_5$$

Minimize SO_2

$$f_2(\vec{X}) = 189.73X_1 + 0.26X_2 + 116.9X_3 + 319.6X_4 + 0.0037X_5 < 626.4937$$

Minimize NOx

$$f_3(\vec{X}) = 55.73X_1 + 32.66X_2 + 74.65X_3 + 1050.79X_4 + 61.69X_5 < 61275.52$$

Minimize TSPM

$$f_4(\vec{X}) = 57.80X_1 + 0.93X_2 + 37.58X_3 + 616.64X_4 + 1.81X_5 < 714.76$$

Such that

$$f_1(\vec{X}) > 2825.000$$
$$f_2(\vec{X}) < 626.4937$$
$$f_3(\vec{X}) < 1275.520$$
$$f_4(\vec{X}) < 714.7600$$

The $f_1(X)$ is an objective function that maximizes the electricity generation. The $f_2(X)$, $f_3(X)$ and $f_4(X)$ minimizes the amount of SO_2, NOx and TSPM emitting from various TPPs respectively. These relations are built using the data presented in Table 1.

Pollution statistics of Delhi TPPs: Delhi is the capital city of India and has a major requirement of electricity. It has many TPPs for generating electricity to meet the demand of the city and the country. These TPPs are producing electricity in different amounts and consuming various fossil fuels in different amounts, thus producing pollutants in different amounts. The detailed pollution statistics of prominent five TPPs in Delhi (Rajesh et al. 2015) is tabulated in Table 1.

SWARM INTELLIGENCE

Swarm intelligence (SI) algorithms have origin from the nature and are iterative search algorithms. The nature has the efficient and robust searching strategy, and the SI algorithms are the mimicking computer programs for the same. Most of the SI algorithms composed of artificial and/or natural individuals that coordinate using decentralized control and self-organization for searching target or food efficiently. Almost all the SI algorithms have shown promising results on standard optimization benchmark problems compared to classical optimization. Few among the SI algorithms are Particle Swarm Optimization (Eberhart & Kennedy 1995b, Eberhart & Kennedy 1995a), Artificial Bee Colony (ABC) (Karaboga 2005, Karaboga & Basturk 2006), Firefly Algorithm (FFA) (Yang 2009), Cuckoo Search Algorithms (CSA) (Yang & Suash 2009) and Grey Wolf Optimizer (Mirjali et al. 2014). Following section explains briefly about the SI algorithms used here for performance comparison.

Particle swarm optimization: Eberhart & Kennedy (Eberhart & Kennedy 1995b, 1995a) have introduced Particle swarm optimization (PSO), one of the SI algorithms introduced in 1995. The PSO exhibits the social life of swarm in nature and is implemented as computer search algorithm (Robinson & Samii 2004). The members of the swarm interact with each other to reach the goal (Sabat et al. 2009). In PSO, every member is called particle and represents the solution in the search range. The movement of the swarm is based on the influence of two best particles called personal best (pbest) and global best (gbest). The personal best (pbest) is the best position of the same articles in its search history and global best (gbest) is the best position of the swarm. The particle's position is evaluated based on the fitness function to be optimized.

Grey wolf optimizer: The Grey wolf optimizer (GWO) is a SI algorithm inspired by the prey hunting behaviour of grey wolves in nature, introduced by Seyedali et al. in 2014 (Mirjali et al. 2014). The Grey wolves generally live in group called pack. These wolves hunt the prey efficiently, since they follow very strict social hierarchy. In the hierarchy, they are divided among themselves as; 1) alphas, 2) beta, 3) omega and 4) delta. The "alphas" enjoy the highest level in the hierarchy and "omega" the lowest. The "alphas" are the strongest in the pack and issue the orders to the group. These wolves have the ability to identify the location of prey and hence whole pack will move and attack. The prime steps of hunting (Mirjali et al. 2014) are: 1) Tracking, chasing and approaching the prey, 2) Pursuing, encircling and harassing the prey until it stops moving, and 3) Attacks the prey. The mathematical model of the wolves for prey hunting and attaching is developed as follows.

The position update equation of the pack is as follows (Mirjali et al. 2014):

$$\vec{D} = \left|\vec{C} \times \vec{X}_p(t) - \vec{X}(t)\right|$$
$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \times \vec{D}$$

Where t is the current iteration, A and C are coefficient vectors, X_p is the position vector of the prey, and X is position vector of a grey wolf. The vectors A and C are calculated as follows:

$$\vec{A} = 2\vec{a} \times r_1 - \vec{a}$$
$$\vec{C} = 2\vec{a}$$

Where components of a is linearly decreased from 2 to 0 with iterations and r_1, r_2 are random vectors in [0, 1].

The whole pack reaches and attack the prey by updating their position based on the location of the alpha, beta and delta.

$$D_\alpha = \left|C_1 * X_\alpha - X\right|$$
$$D_\beta = \left|C_1 * X_\beta - X\right|$$
$$D_\delta = \left|C_1 * X_\delta - X\right|$$
$$X_1 = X_\alpha - A_1 * D_\alpha$$
$$X_2 = X_\beta - A_1 * D_\beta$$
$$X_3 = X_\delta - A_1 * D_\delta$$
$$X(t+1) = \frac{X_1 + X_2 + X_3}{3}$$

Weighted distance grey wolf optimizer: The weighted distance grey wolf optimizer (Malik et al. 2015) is a variant of grey wolf optimizer (Mirjali et al. 2014). The grey wolf optimizer (GWO) algorithm was developed by Seyedali et al. (2014), that mimics the prey hunting mechanism of grey wolf. The location update of all the wolves in pack is done by a simple average of three best locations of the pack and whole pack follows it. The weighted distance grey wolf optimizer (WdGWO) (Malik et al. 2015) updates the location of the wolves in the pack that is influenced by the weighted best locations of the leaders in the pack. In WdGWO algorithm, the position update equation is weighted in every iteration. The weights w_i are calculated based on coefficient vectors A_i and C_i as per equations (Malik et al. 2015). The location update equation is modified as per the calculated weights, shown in following equation. This strategy is particularly very helpful in optimizing complex problems.

$$w_1 = A_1 * C_1, \quad w_2 = A_2 * C_2, \quad w_3 = A_3 * C_3 \qquad ...1$$

$$X(t+1) = \frac{w_1 * X_1 + w_2 * X_2 + w_3 * X_3}{w_1 + w_2 + w_3} \qquad ...2$$

The WdGWO is integrated with non-dominated sorting. The two solutions are said to be non-dominated if none of them has less value in all objectives (in a minimization problem). It maintains an archive for maintaining Pareto optimal front as in Layak et al. (2015). The detailed algorithm and archive update strategy is explained in the Algorithm 1.

***Algorithm 1*: Pseudo code for proposed WdGWO**

1: Initialize iteration count (MaxIter)
2: Initialize size of the pack (NG)
3: Initialize grey wolf population X
4: Initialize a, A and C
5: Initialize archive size to 100
6: Evaluate fitness of each grey wolf $f_i(X)$
7: Compute X_α = the first best grey wolf
8: Compute X_β = the second best grey wolf
9: Compute X_δ = the third best grey wolf
10: While t <= MaxIter do
11: Update a, A and C
12: Update X_α, X_β and X_δ
13: Calculate weights (w_l)
14: Update position vector $X(t+1)$
15: Evaluate fitness $f_i(X)$
16: Find Pareto optimal solution
17: Check domination of new solution in archive
18: If dominant, update archive
19: If archive size exceeds
20: Use crowding distance to maintain archive
21: End while
22: Report results

The algorithm first starts with all initializations like maximum iterations (1000), size of the pack (20) and the whole pack location is randomly initialized with Gaussian distribution random strategy. Immediately the best three wolves are recorded and then searching starts. During the search process, the fitness of each wolf will be calculated; from this the best locations of three wolves are updated and recorded. The updated best grey wolves further enhance the search process. An archive of size 100 is maintained to retain the Pareto dominated solution. The size of the archive is maintained constant, if the solution exceeds the limit, then archive crowding distance concept is used to maintain the archive.

SIMULATION SETUP

The code for presented algorithm PSO (Eberhart & Kennedy 1995b, 1995a), GWO (Mirjali et al. 2014) and WdGWO algorithm (Malik et al. 2015) is written in Matlab 7.2. The WdGWO algorithm is first applied on standard mutliobjective optimization benchmark problems like KUR, FON and SCH. The algorithms are then applied for optimizing TPP problem. The results are documented and presented in two forms, numerical and graphical. The definitions of these problems are explained in the following section.

Benchmark problems: The following is the definition of well-known standard multi-objective problems.

KUR problem:

$$f_1(x) = \sum_{i=1}^{n-1} -10\exp(-0.2(\sqrt{x_i^2 + x_{i+1}^2}))$$

$$f_2(x) = \sum_{i=1}^{n} (|x_i|^{0.8} + 5\sin(x_i^3))$$

FON problem:

$$f_1(x) = 1 - (\exp(-\sum_{i=1}^{n}(x_i - \frac{1}{\sqrt{3}})^2)$$

$$f_2(x) = 1 - (\exp(-\sum_{i=1}^{n}(x_i + \frac{1}{\sqrt{3}})^2)$$

SCH problem:

$$f_1(x) = x^2$$

$$f_2(x) = (x-2)^2$$

A set of performance metric (Huang et al. 2006) is used to measure the efficiency of GWO (Malik et al. 2015) and WdGWO (Malik et al. 2015), like convergence metric, inverted generational distance metric and convergence graphs.

Performance metrics: The brief definition of multi-objective performance metrics is explained in the following section.

***Convergence metric (CM)*:** The CM measures the extent of convergence of Pareto solutions to the known optimal Pareto front. It is defined as (Huang et al. 2006):

$$CM = \frac{1}{n}\sum_i d_i$$

Where n is the number of non-dominated solutions obtained by the algorithm and d_i is the Euclidean distance (in objective space) between the i^{th} non-dominated solution and the nearest member of the known Pareto optimal front. A smaller value of CM denotes a better convergence performance.

***Inverted generational distance metric (IGD)*:** The IGD is used to estimate the closeness of elements in dominated solutions to those in the true Pareto optimal set. It is defined as (Huang et al. 2006).

$$GD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{n}$$

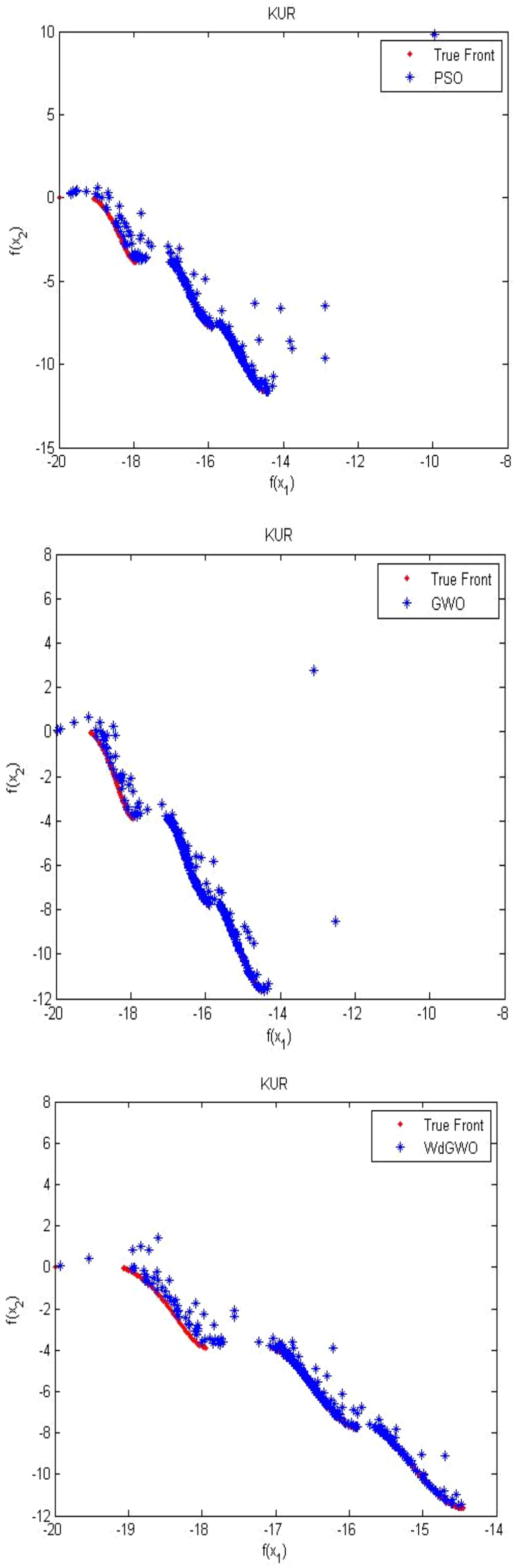

Fig. 1: Pareto fronts on KUR function.

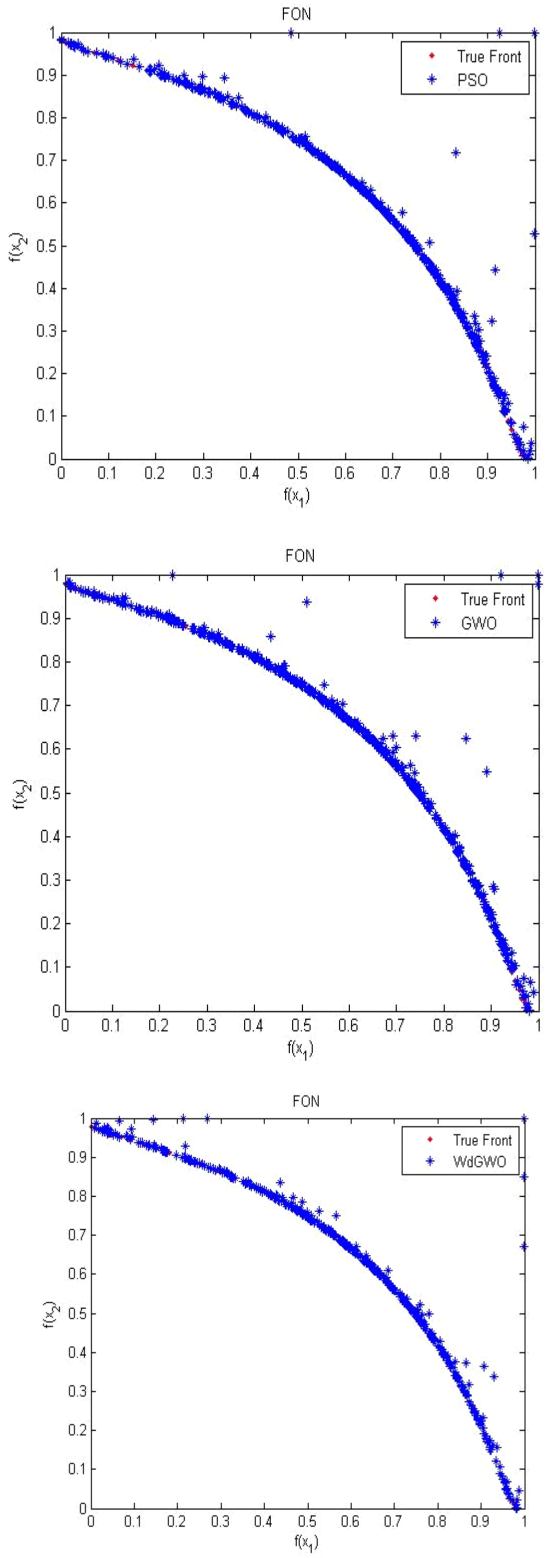

Fig. 2: Pareto fronts on FON function.

Where n is number of non-dominated solutions generated by the algorithm and d_i is the Euclidean distance between the elements in Pareto optimal set found so far (by the algorithm) and its nearest neighbour in known Pareto optimal solution. A smaller IGD value indicates better performance.

***Convergence graphs*:** The convergence characteristics of optimizing algorithms can be found out using Pareto front graphs. If the obtained Pareto front of the algorithm is closer to the true Pareto front, then algorithm is said to converged.

RESULTS AND DISCUSSION

All the algorithms are initialized with population size of 100 in the search range. The stopping criteria for all the algorithms are set to the maximum number of iterations. The results obtained are the average of 25 trials and each trial is of 1000 iterations. The GWO and WdGWO are validated on standard benchmark problems and the results are presented in Tables and Pareto front obtained by these algorithms is shown in Figures.

Results on benchmark problems: The numerical results on standard multiobjective benchmark problems are presented in Table 2. This table shows CM and IGD values obtained by PSO, GWO and WdGWO algorithms on KUR, FON and SCH problems.

From Table 2, it is seen that WdGWO algorithm shows better performance. The PSO also performed well compared to GWO. The WdGWO is a variant of GWO, and the table shows great improvements by WdGWO compared to GWO and even performed well compared to PSO. The convergence of algorithms to the optimal solution is depicted as graphs from Fig. 1 to Fig. 3. The Fig. 1 shows Pareto front obtained by algorithms on KUR problem along with its true Pareto front. From this figure it is seen that WdGWO algorithm obtained good Pareto front. The Fig. 2 and Fig. 3 show the similar characteristics on FON and SCH problems respectively. An appreciable Pareto front is obtained by WdGWO on both the problems (FON and SCH) compared to GWO and PSO.

Results on TPP problem: The WdGWO algorithm is further validated on TPP problem. The definition of TPP problem is given above. The TPP problem is formulated as a quad multiobjective problem comprising four objectives, viz. maximizing electricity production, minimizing SO_2, NOx and TSPM. As there are four objectives involved for simultaneous optimization, it is difficult to present pictorial graphs, hence only numerical values are presented for comparison. The best ten results of all the algorithms are documented and presented in Table 3 to Table 5. The Table 3 shows the ten best results obtained by PSO. The Table 4 shows the ten best results obtained by GWO and similarly

Table 1: Delhi thermal power plant specification.

TPP	Power (MW)	SO_2 (mg/m^3)	NOx (mg/m^3)	TSPM (mg/m^3)
Rajghat	135	189.73	55.73	57.80
IGT	1500	0.26	32.66	0.93
IP	135	116.90	74.65	37.58
Badarpur	705	319.60	1050.79	616.64
Pragati	350	0.0037	61.69	1.81
Total	2825	626.4937	1275.52	714.76

Table 2. Results on benchmark problems.

Problem	Metrics	PSO	GWO	WdGWO
KUR	CM	0.00168	0.00185	0.00163
	IGD	0.03361	0.03920	0.03110
FON	CM	0.61900	0.61700	0.61600
	IGD	18.2000	18.4000	18.1000
SCH	CM	0.64000	0.64100	0.63400
	IGD	18.8000	18.9000	17.9000

Table 3: Optimized results by PSO.

Power (MW)	SO_2 (mg/m^3)	NOx (mg/m^3)	TSPM (mg/m^3)
2932.203	432.0804	1112.959	590.3320
3093.151	467.2138	1184.489	630.4154
3959.684	489.0875	1014.528	520.7439
4216.559	698.9127	1293.031	693.7305
3831.157	553.3960	1185.907	626.5501
3831.157	553.3960	1185.907	626.5501
3369.338	534.4768	931.3854	499.2697
4315.189	651.3697	1176.983	618.4074
2883.034	236.8838	625.9071	404.6362
2917.362	366.4866	1152.322	620.9660

Table 4: Optimized results by GWO.

Power (MW)	SO_2 (mg/m^3)	NOx (mg/m^3)	TSPM (mg/m^3)
3600.687	557.6702	1036.346	546.4492
4382.540	619.6681	1293.754	707.6061
3519.554	570.9630	841.7102	444.0282
2903.436	643.6155	1210.379	734.2941
3149.049	342.3880	761.1904	382.6040
3023.030	350.5322	634.4319	309.9173
3236.082	563.9527	1128.380	609.5181
3642.230	652.6109	1308.885	710.6673
4301.354	622.1914	1114.070	615.0904
2967.189	529.4395	963.2618	538.3525

Table 5 shows the ten best results obtained by WdWGO. The best and the least results among the recorded results are again compared separately in Table 6 and Table 7. The Table 6 shows that electricity production (4663.9) obtained by WdGWO is far better than the other algorithms and even for better than original present amount (2825). From the same table it is seen that the total pollution liberated after applying WdGWO is far less (2422.5) than the state of-the-

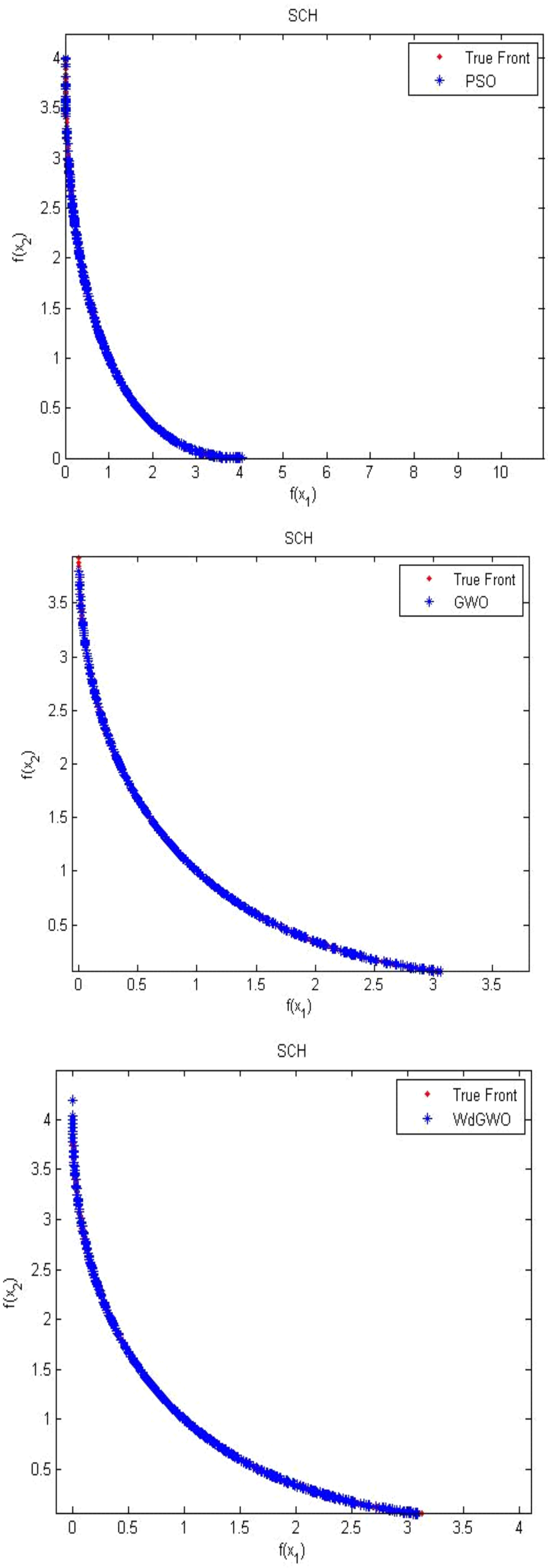

Fig. 3: Pareto fronts on SCH function.

Table 5: Optimized results by WdGWO.

Power (MW)	SO_2 (mg/m³)	NOx (mg/m³)	TSPM (mg/m³)
4057.305	662.7847	1085.262	570.9026
3982.827	662.4117	1175.721	641.1828
3960.465	573.9367	1019.332	530.0648
4663.901	604.7561	1125.249	692.5082
3414.029	404.6717	838.5779	419.1541
3810.209	582.7276	1117.347	603.7302
3611.450	546.6452	983.4271	517.8532
4223.601	546.3151	1157.205	597.6016
3048.523	289.8067	634.9630	304.9539
4033.930	504.9116	1072.909	550.3648

Table 6: Best results comparison.

	Original	GP	PSO	GWO	WdGWO
Power (MW)	2825	3067.7	4315.19	4382.54	4663.9
SO_2 (mg/m³)	626.4937	625.9737	651.37	619.67	604.76
NOx (mg/m³)	1275.52	1210.2	1176.98	1293.75	1125.25
TSPM (mg/m³)	714.76	712.9	618.41	707.61	692.51
Total Pollution	2616.774	2549.074	2446.8	2621	2422.5

Table 7: Least results comparison.

	Original	GP	PSO	GWO	WdGWO
Power (MW)	2825	3067.7	2883.03	2903.44	3048.52
SO_2 (mg/m³)	626.4937	625.9737	236.89	643.62	289.81
NOx (mg/m³)	1275.52	1210.2	625.91	1210.38	634.96
TSPM (mg/m³)	714.76	712.9	404.64	734.23	304.95
Total Pollution	2616.774	2549.074	1267.4	2588.2	1229.7

Table 8: Maximized Power (Minimized pollution)

PSO	GWO	WdGWO
2932.2 (2135.4)	3600.7 (2140.5)	4057.3 (2318.9)
3093.2 (2282.1)	4382.5 (2621.0)	3982.8 (2479.3)
3959.7 (2024.4)	3519.6 (1856.7)	3960.5 (2123.3)
4216.6 (2685.7)	2903.4 (2588.3)	4663.9 (2422.5)
3831.2 (2365.9)	3149.0 (1486.2)	3414.0 (1662.4)
3831.2 (2365.9)	3023.0 (1294.9)	3810.2 (2303.8)
3369.3 (1965.1)	3236.1 (2301.9)	3611.4 (2047.9)
4315.2 (2446.8)	3642.2 (2672.2)	4223.6 (2301.1)
2883.0 (1267.4)	4301.4 (2351.4)	3048.5 (1229.7)
2917.4 (2139.8)	2967.2 (2031.1)	4033.9 (2128.2)

art algorithms. Similarly, the Table 7 also depicts the same order of performance. The Table 8 shows the summary of the results shown by various algorithms. It shows electricity production and the total pollutants in parenthesis.

Since TPP problem is formulated as multiobjective optimization problem and there are many results obtained with various amounts of electricity production and pollution liberated giving different options for selecting a required strategy.

CONCLUSION

This paper addresses the current issue of power demand and air pollution in a novel way. Most of the power is produced in thermal power plants and this causes the poisonous pollutants to be liberated in the air due to burning of fossil fuels. This causes a drastic change in the environment and has an adverse effect on human health. Since the alternate ways of clean air, electricity production is almost non-feasible at this juncture, hence improving the efficiency of the existing source is inevitable and encouraged. The strategies for better efficiency may be obtained by constructing a mathematical model for existing TPPs. The demand itself shows that, there are two objectives (electricity production and pollution reduction) to be addressed simultaneously; they are interlinked and non-separable. Hence this paper presents the new mathematical model comprising of multiple objectives for increasing electricity production and reducing air pollution. For increasing electricity production only one objective is developed and for pollutants more than one objective are developed, as the causes of air pollution are many, like SOx, NOx and TSPM. The developed multiobjective optimization problem is difficult to handle by classical optimizing methods; this paper integrate the well-known Swarm intelligence (SI) algorithms to address the issue. It integrates weighted distance grey wolf optimizer (WdGWO) on Delhi thermal power plant (TPP). The WdGWO is one of the SI algorithms that have proved well on standard single objective benchmark optimization problems. Here the WdGWO is first applied on standard multiobjective benchmark optimization problems along with its state of-the-art to validate its usage in TPP problem. The results shown by WdGWO algorithm on benchmark problems are better than the state of-the-art and encourages its usage for TPP problem. The results obtained by SI algorithms on TPP problem have given lots of options to be implemented with various amounts of electricity production and pollutants that are emitted. Thus the integration of WdGWO algorithms for TPP problem increases electricity production and minimizes the air pollution drastically.

REFERENCES

Basu, M. 2010. Economic environmental dispatch of hydrothermal power system. Electric Power and Energy Systems, 32: 711-720.

Bonnans, J. F., Gilbert, J. C., Lemaréchal, C., and Sagastizábal, C. A. 2003. Numerical Optimization: Theoretical and Practical Aspects. Springer.

Civicioglu, P. 2013. Artificial cooperative search algorithm for numerical optimization problems. Information Sciences, 229: 58-76.

Devi, R., Dahiya, R., Gadgil, K., Singh, V., and Kumar, A. 2007. Assessment of the temporal variation of ambient air quality in a metropolitan city in India April 2007. Available: http://www.ecoweb.com/editorial/070429.html.

Eberhart, R. and Kennedy, J. 1995a. A new optimizer using particle swarm theory. Proceedings of 6th Int. Symp. Micro Machine and Human Science (MHS), Cape Cod, MA, pp. 39-43 (November).

Eberhart, R. and Kennedy, J. 1995b. Particle swarm optimization. Proceedings of IEEE Int. Conference on Neural Networks, Piscataway, NJ, pp. 1114-1121 (November).

Fletcher, R. 2000. Practical Methods of Optimization. John Wiley and Sons.

Huang, V., Suganthan, P. and Liang, J. 2006. Comprehensive learning particle swarm optimizer for solving multi-objective optimization problems. International Journal of Intelligent Systems, 21(2): 209-211.

Karaboga, D. 2005. An idea based on honey bee swarm for numerical optimization. Report No. TR06, Computer Engineering Department, Engineering Faculty, Erciyes University, Turkey.

Karaboga, D. and Basturk, B. 2006. An artificial bee colony (abc) algorithm for numeric function optimization. IEEE Swarm Intelligence Symposium, Indianapolis, Indiana, USA (May).

Knowles, J. 2006. Parego: a hybrid algorithm with on-line landscape approximation for expensive multiobjective optimization problems. IEEE Transactions on Evolutionary Computation, 10(1): 50-66.

Layak, A., Samrat, L,S. and Siba, K.U. 2015. Particle swarm optimisation with adaptive neighbourhood search for solving multi-objective optimization problems. International Journal of Swarm Intelligence, (Inderscience), 1(1).

Le, K. D., Golden, J. L., Stansberry, C. J., Vice, R. L., Wood, J. T., Ballance, J., et al. 1995. Potential impacts of clean air regulations on system operations. IEEE Transaction on Power Systems, 10: 647-653.

Malik, M.R.S., Mohideen, E.R. and Layak, A. 2015. Weighted distance grey wolf optimizer for global optimization problems. Proceedings of the IEEE International Conference on Computational Intelligence and Computing Research, Tamilnadu, India, 1-6 (December).

Mirjali, S., Mirjali, S.M. and Lewis, A. 2014. Grey wolf optimizer. Advances in Engineering Software, 69(0): 46-61.

Rajesh, D., Arvind, K. and Vivek, N. 2015. On optimization of air pollution and electricity production of thermal power plants of Delhi using goal programming. Journal of Energy Techn. & Policy, 5(2): 84-88.

Robinson, J. and Samii, Y.R. 2004. Particle swarm optimization in electromagnetic. IEEE Transactions on Antenna and Propagation, 52(2): 397-400.

Sabat, S.L., Layak, A. and Udgata, S.K. 2009. Adaptive accelerated exploration particle swarm optimizer for global multimodal functions. Proceedings of the World Congress on Nature and Biologically Inspired Computing, Coimbatore, India, 654-659 (December).

Vanderbei, R.J. 2008. Linear Programming: Foundations and Extensions, International Series in Operations Research and Management Science. 3rd edition, Springer.

Wan-Kuen, J. and Joon-Yoeb, L. 2006. Indoor and outdoor levels of respirable particulates (PM10) and carbon monoxide (CO) in high rise apartment buildings. Atmospheric Environment, 40: 6067-6067.

Yang, X.S. 2009. Firefly algorithms for multimodal optimization. Proceedings of the 5th International Conference on Stochastic Algorithms: Foundations and Applications. SAGA'09, Berlin, Heidelberg, Springer-Verlag, 169-178.

Yang, X.S. and Suash, D. 2009. Cuckoo search via lvy flights. Proc. of the World Congress on Nature & Biologically Inspired Computing (NaBIC 2009), Coimbatore, India, IEEE Publications, 210-214.