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WEIGHTED DISTANCE GREY WOLF OPTIMIZER TO CONTROL AIR POLLUTION OF DELHI THERMAL POWER PLANT

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ABSTRACT

Due to rapid growth in Industrialization and Urbanization, there is an exponential increase in the air pollution. This increased air pollution has major impact on environment and human health. The growth in industrialization and urbanization has everlasting demand of electricity. Most of the electricity (almost 60%) to meet the said demand comes from Thermal Power Plants (TPP). Almost all the TPPs generate electricity by burning fossil fuels which releases poisonous gas in the air contributing to pollution. The air pollution caused by TPPs may be reduced by using non-conventional energy source like solar and wind, unfortunately they are in their infancy, and thus the tuning and optimizing existing TPPs are of prime importance to reduce the air pollution. To device the alternate strategies, one need to have a mathematical model that depicts the performance of existing TPPs. There are many mathematical ways to model optimization of air pollution in TPPs. Since such models turns out to be nonlinear, complex and multimodal, hence most of the classical optimization methods fail to give appropriate solution. This paper integrates an efficient variant of Nature Inspired (NI) algorithm namely weighted distance grey Wolf Optimizer (WdGWO) for minimizing air pollution caused by Delhi Thermal Power Plants. The results show that the WdGWO has reduced total pollution by 8.2350% as compared to the state of-the-art which has reduced even less than 4% only. Thus results support the application and superiority of WdGWO algorithm for Delhi TPPs.

INTRODUCTION

The Air pollution has hazardous effect on both environment and human health and is a serious concern of the 22nd century (IEEE working group, 1995). The poisonous air pollutants are mainly due to the rapid industrialization and urbanization. This rapid growth demands sustained power and hence there is an exponential growth in electricity consumption and generation and generation. The major portion of electricity is produced by burning of fossil fuels in thermal power plants (TPP). The fossil fuels like coal, petrol, diesel and kerosene etc. are major source of thermal energy due to their high calorific value and are available in abundant. A large amount of fossil fuels are burnt in TPP to produce electricity which causes huge amount of air pollution (Basu, 2010). The major harmful gases and pollutants released in air are Sulphur Dioxide (SO_2), Oxides of Nitrogen (NOx) and Total Suspended Particulate Matter (TSPM). Though there are many ways to avoid the release of poisonous gases from TPPs by making use of non-conventional energy sources (solar, wind etc.), but they are still in their infancy. Due to many good reasons, the establishment of new TPP is not possible and the hence control strategies for existing TPP is very much in demand. Thus it is on the radar of government and researchers to device strategies to reduce air pollution without effecting electricity production. This can be achieved by constructing mathematical model of air pollution reduction strategies. There are many mathematical models available to reduce air pollution from existing TPP. These equivalent models have nonlinear, complex and multimodal characteristics. Due to the complexity involved in optimization most of the classical optimization methods fail to gives required solution (Fletcher, 2000; Bonnans JF and Sagastizabal, 2003; Vanderbei, 2008) and hence alternatives like Nature Inspired (NI) algorithms may be preferred.

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The previous works show poor results due to their inherent capability; they find difficulty in optimizing the problems that have non separable and strongly dependent nature among the variable in the problem.

The NI algorithms are the optimizing paradigms developed by mimicking nature's searching behavior and used for solving complex optimization problems (Ali et al., 2012; Rajesh et al., 2015; Civicioglu, 2013; Sabat et al., 2009; Goldberg, 1989; Eberhart and Kennedy, 1995a, b; Karaboga, 2005; Karaboga and Basturk, 2006; Yang and Suash, 2009). Many NI algorithms have proved well on standard benchmark optimization problems and opens the door for their usage to real world applications. This paper uses an efficient NI algorithm called weighted distance grey wolf optimizer (WdGWO) (Malik et al., 2015), a variant of GWO (Seyedali et. al., 2014) for reducing air pollution without affecting the amount of electricity being produced by Delhi TPP. Since NI algorithms including WdGWO, have stochastic behavior, hence can easily solve the complex problem problems. The rest of paper is organized as follows: First the brief explanation about TPP and Air pollution is given. Then the problem formulation and TPPs pollution statistics is presented. The WdGWO algorithm is explained followed by the detailed set used for simulation and algorithms used for comparison. The obtained results are discussed in details followed by conclusions in the last part.

Tpp and air pollution

The major source of power generation among all other sources is the TPPs. The TPPs usually convert heat energy to electric power. The heat energy generated by burning of fossil fuels used for driving steam turbines and an electrical generator. The process of burning fossil fuels causes the poisonous gases to be liberated in the air and hence cause the pollution. Following section describes both TPPs and air pollution in details.

THERMAL PLOWER PLANT

The TPPs accounts for major part of electricity generation in the world and India in particular. The online literature (Wikipedia, 2016) reveals that, the energy policy of India is largely defined by the country's burgeoning energy deficit and increased focus on developing alternative sources of energy, particularly nuclear, solar and wind energy. About 70% of India's energy generation capacity is from fossil fuels, with coal accounting for 40% of India's total energy consumption followed by crude oil and natural gas at 24% and 6% respectively. India is largely dependent on fossil fuel imports to meet its energy demands; by 2030 India's dependence on energy imports is expected to exceed 53% of the country's total energy consumption. In 2009-10, the country imported 159.26 million tones' of crude oil which amount to 80% of its domestic crude oil consumption where as 31% of the country's total imports are due to oil. To save primary energy resources i.e. to reduce fuel consumption, and to reduce emissions, maximum power plant efficiency is a crucial parameter.

The TPPs generally consist of three main elements which are boiler, turbine, an alternator, and other complementary accessories such as a fuel handling system, water handling, and emission control system. The construction of a new thermal power plant is relatively reduced. Recently, there have been concerns regarding the efficiency improvement of existing thermal power plants. The efficiency of such type of power plant is very low and great amount of loss in thermal energy may be noticed (Kumar et al.) In order to generate a required electric energy, the turbine needs an equivalent amount of thermal energy in addition to the loss. Minimizing the loss leads to a reduction of pollutants in the environment as well as production cost.

AIR POLLUTION

Air pollution is a state of air containing chemicals like gases, dust, fumes or odor in the atmosphere that has harmful effects. The substances that cause air pollution are called pollutants. Air pollution consists of gaseous, liquids, or solid substances that, when present in sufficient concentration, for a sufficient time, and under certain conditions, tend to interfere with human comfort, health or welfare, and cause environmental damage. Air pollution causes acid rain, ozone depletion, photochemical smog, and other such phenomena. The large amount of electricity is produced from thermal power plants, where the coal and other fossil fuels are burnt extensively to boil water and thus produce electricity. In addition to electricity, the poisonous gases like SO_2, NOx and TSPM are also produced as a byproduct. The detailed about these poisonous gases is explained in the following section.

Sulphur Dioxide (SO_2)

It is a poisonous compound and has chemical formula SO_2. In general and standard atmosphere, it has a pungent and irritating smell. It enters the atmosphere in two ways, both man-made and natural phenomena; combustion of fossil fuels, oxidation of organic material in soils, volcanic eruptions and biomass burning. Its presence in the atmosphere in any quantity is injurious and is a qualitative pollutant.

Oxides of Nitrogen (NO_X)

It is generic term referred for the mono and dioxide of Nitrogen (NO nitric oxide and NO_2 nitrogen dioxide). It is a byproduct liberated from the reaction among nitrogen, oxygen and even hydrocarbons (during combustion), especially at high temperatures. These are quantitative pollutants and harmful to human health. It reacts with the oxygen in the air resulting in ground-level ozone. The ground-level ozone has very harmful effect on human health especially on the respiratory system. It also reacts to form nitrate particles, and acid aerosols. It may react with water can cause acid rain and the deterioration of the quality of water.

Total Suspended Particulate Matter (TSPM)

Particulate matter is the term used for solid or liquid particles found in the air. Some particles are large or dark enough to be seen as soot or smoke. Others are so small they can be detected only with an electron microscope, their chemical and physical compositions vary widely. Particulate matter can be directly emitted or can be formed in the atmosphere when gaseous pollutants such as SO_2 and NOx react to form fine particles. The presence of these in the atmosphere with the particle sizes ranging from less than 0:01m to more than 100 m is harmful to human health (Devi et al.; Wan-Kuen and Joon-Yoeb, 2006; Rajesh et al., 2015).

Probleam formulation and pollution statistics

This section discusses the mathematical model of Delhi TPPs for reducing air pollution, the data related to TPPs and constraints handling methods.

MATHEMATICAL MODEL FOR DELHI TPPs

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 in developing countries like India. Hence there is a requirement of finding a sustainable solution which may not reduce electricity production but must reduce the increasing pollutants. This paper proposes a single objective constraints 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 for pollutant reduction. There are mainly five TPPs operating in Delhi (India) to provide required electricity demand of the country. This paper considers the five TPPs viz. Rajghat, Indraprasth Gas Turbine (IGT), Indraprasth (IP), Badarpur and Pragati power station. The following equations may be built to minimize the air pollution and maximize the electricity generation (Rajesh et al., 2015).

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

Such that:

$$g_1(\vec{X}) = 189.73X_1 + 0.26X_2 + 116.9X_3 + 319.6X_4 + 0.0037X_5 < 626.4937$$
$$g_2(\vec{X}) = 55.73X_1 + 32.66X_2 + 74.65X_3 + 1050.79X_4 + 61.69X_5 < 61275.52$$
$$g_3(\vec{X}) = 57.80X_1 + 0.93X_2 + 37.58X_3 + 616.64X_4 + 1.81X_5 < 714.76$$

The f(X) is an objective function that maximizes the electricity generation. The $g_1(X)$, $g_2(X)$ and $g_3(X)$ are the constraints that minimizes the amount of SO_2, NOx and TSPM emitting from various TPPs respectively.

CONSTRAINTS HANDLING

Since the modeled TPP problem involves constraints to be satisfied, hence it is worth mentioning general constraints handling strategies. The generic optimization problem with constraints can be expressed as

Finding $\vec{x} = (x_1, x_2, x_3 \ldots, x_D)$

That optimizes $f(\vec{x})$

Subject to:

$$g_i(\vec{x}) < 0, \quad i = 1, 2, \ldots, q$$
$$h_i(\vec{x}) = 0, \quad i = q+1, q+2, \ldots, m$$

Where $l_i < x_i < u_i \quad i = 1, 2, \ldots, D$

Where "f" is the objective function, "g_i" and "h_i" is the inequality and equality constraints respectively.

The values "l_i" and "u_i" for all "i" belongs to "D" are the lower and upper bounds of the solution defining the search space.

The usual way of handling constraints is to convert constrained optimization problem into an unconstrained problem. Then any unconstrained optimization algorithms may be applied without loss of generality. This conversion from constraint to unconstraint is implemented with the introduction of penalty function as

$$\phi(x) = f(x) + r_k \varphi(g_i(x); \quad i = 1, 2, \ldots, m)$$

Where "$\phi \geq 0$" is a real valued function that imposes a penalty. The penalty on each constraint is imposed by the penalty factor "r_k". Although the above penalty method works well for certain constrained optimization problems, selecting the penalty factor "r_k" remains a challenge. If the penalty factor is chosen to be too small, an infeasible solution may not be penalized enough (underpenalization), resulting a final infeasible solution. If the penalty factor is too large, a feasible solution is very likely to be found (overpenalization), but could be of poor quality (Runarsson and Yao, 2000). Thus underpenalization and overpenalization are not good for handling constraints.

Despite its simplicity, a penalty function requires the definition of penalty factors to determine the severity of the penalization, and these values depend on the problem being solved (Runarsson and Yao, 2000). Due to this major disadvantage, several alternative constraint-handling algorithms have been proposed. Stochastic ranking technique has been proposed (Runarsson and Yao, 2000) to maintain the required balance between objective function and penalty function. This technique uses stochastic bubble-sort algorithm to rank the individuals for generating offspring's for the next generation. In order to solve complex constrained problems, WdGWO algorithm is hybridized with stochastic ranking (Runarsson and Yao, 2000). Similarly the stochastic ranking is hybridized with GWO algorithm and PSO algorithm for comparison (Layak et al., 2012).

POLLUTION STATISTICS OF DELHI TPPs

Delhi is the capital city of India and has 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 amount, 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.

NATURE INSPIRED ALGORITHMS

Nature Inspired (NI) algorithms, are the iterative search algorithms that has origin from nature. The nature has the efficient and robust searching strategy; the NI algorithms are the mimicking computer program for the same.

Most of the NI 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 NI algorithms have shown promising results on standard optimization benchmark problems compared to classical optimization. Few among the NI algorithms are Particle Swarm Optimization (Eberhart and Kennedy, 1995a,b), artificial bee colony (ABC) (Karaboga, 2005; Karaboga and Basturk, 2006), Firefly Algorithm (FFA) (Xin-She Yang, 2009) and Cuckoo search algorithms (CSA) (Yang and Suash, 2009).

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

WEIGHTED DISTANCE GREY WOLF OPTIMIZER

The Weighted distance Grey Wolf Optimizer (Malik et. al., 2015) is a variant of Grey Wolf Optimizer (Seyedali et al., 2014). The grey wolf optimizer (GWO) (Seyedali et al., 2014) is one of the NI algorithm developed by Seyedali et al., in 2014, that mimics the prey hunting mechanism of grey wolves.

The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Using the hierarchy of wolves, GWO implement four main steps of hunting, searching, encircling, and attacking the prey (Seyedali et al., 2014). The GWO defines mainly four types of grey wolves such as alpha, beta, delta, and omega to simulate the leadership hierarchy for hunting the prey as they have the ability to identify location of prey. The movement of the whole pack of wolves will be guided by the above wolves. The location update of all the wolves in pack is done by simple average of three best location of the pack and whole pack follows it.

This paper uses a weighted distance method for updating location vector of the pack, hence called WdGWO (Malik et al., 2015). The location of the wolves in the pack is influenced by the weighted best locations of the leaders in the pack. The weights are calculated in every iteration based on the coefficient vectors.

In WdGWO algorithm, the position update equation is weighted in every iteration as shown in following equations. The weights "w_i" are calculated based on coefficient vectors "A_i" and "C_i" as per equation (2) and equation (1) respectively. The location update equation is modified as per the calculated weights, shown in equation (3). This strategy particularly very helpful in optimizing complex problems.

$$A_1 = 2a * r_1 - a, \quad C_1 = 2r_2$$
$$A_2 = 2a * r_1 - a, \quad C_2 = 2r_2$$
$$A_3 = 2a * r_1 - a, \quad C_3 = 2r_2$$
$$D_\alpha = |C_1 * X_\alpha - X|$$
$$D_\beta = |C_1 * X_\beta - X| \tag{1}$$
$$D_\delta = |C_1 * X_\delta - X|$$
$$X_1 = X_\alpha - A_1 * D_\alpha$$
$$X_2 = X_\beta - A_1 * D_\beta$$
$$X_3 = X_\delta - A_1 * D_\delta$$

$$w_1 = A_1 * C_1, \quad w_2 = A_2 * C_2, \quad w_3 = A_3 * C_3 \tag{2}$$

$$X(t+1) = \frac{w_1 * X_1 + w_2 * X_2 + w_3 * X_3}{w_1 + w_2 + w_3} \tag{3}$$

The WdGWO (Malik et al., 2015) is explained in the Algorithm 1.

Algorithm 1 Pseudo code for proposed SRWdGWO

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: Evaluate fitness of each grey wolf f(X)

6: Compute X_α=the first best grey wolf

7: Compute X_β=the second best grey wolf

8: Compute X_δ=the third best grey wolf

9: While t <=MaxIter do

10: While i <=NG do

11: Update the position of the current grey wolf

12: End while (for i)

13: Update a, A and C

14: Update X_α, X_β and X_δ

15: Calculate weights as per equation (2)

16: Update position vector as per equation (3)

17: Evaluate fitness of each grey wolf f(X)

18: Evaluate constraints of each grey wolf g(X)

19: Check for feasible solution

20: Update penalty factor (Stochastic Ranking)

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 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 and final results are recorded.

SIMULATION SETUP

The code for presented algorithms are written in Matlab 7.2 installed on computer with Core 2 Duo processor and 2GB RAM on a Windows-XP platform. The NI algorithms used for comprehensive performance analysis are Stochastic Ranking Particle Swarm Optimization (SRPSO) (Layak et al., 2012), Goal Programming (GP) (Rajesh et al., 2015), GWO (Seyedali et al., 2014) and WdGWO (Malik et al., 2015) hybridized with Stochastic Ranking.

STOCHASTIC RANKING PARTICLE SWARM OPTIMIZATION

The SRPSO (Layak et al., 2012) is a variant of PSO (Eberhart and Kennedy, 1995a, b) integrated with Stochastic Ranking (Runarsson and Yao, 2000) for handling standard constraints benchmark optimization problems. The PSO is a NI algorithm developed in 1995 by Kennedy and Eberhart that mimics the food searching behavior of flock of birds or fish school. It has proved to be one of the good algorithms to solve complex optimization problems.

GOAL PROGRAMMING

The Goal Programming (GP) is an optimization technique which treats the constraints of linear programming problem as their goal. It was first in 1955 by Charnes and Cooper (Charnes et al., 1955). It has played a vital role for many years to solve many real world problems.

GREY WOLF OPTIMIZER

The GWO is also a nature NI algorithm developed in 2014 by (Seyedali et. al., 2014). The GWO mimics the prey hunting mechanism of Grey wolves. The grey wolves first locate the prey, they encircle and exploit, and then they attack. This strategy was extracted and implemented as computer algorithm for solving global optimization problems (Seyedali et al., 2014; Malik et al., 2015).

Table 2. Delhi Thermal Power Plant Results

	Original	GP	SRPSO	GWO	WdGWO
Amount of SO_2 (mg/m^3)	626.4937	625.9737	578.9892	620.0220	514.6601
Amount of NOx (mg/m^3)	1275.52	1210.2	1245.5730	1271.7679	1209.3813
Amount of TSPM (mg/m^3)	714.76	712.9	694.9890	712.6989	677.2412
Total Pollutants (mg/m^3)	2616.7737	2549.0737	2519.5512	2604.4888	2401.2826

RESULTS AND DISCUSSION

All the algorithms are initialized with population size of 20 in the search range. The stopping criteria for all the algorithms are set to maximum number of iterations (1000). The results obtained are the average of 25 trials and each trial is of 1000 iterations. The algorithms are run for several times to find the good configuration and results are documented in Table 2. From the Table 2 it is seen that the WdGWO shows good results compared to other algorithms. The amount of SO_2 liberated by WdGWO strategy is 514.6601 mg/m^3 which is far less than SRPSO (Layak et al., 2012) (578.9892 mg/m^3), GP (Rajesh et al., 2015) (625.9737 mg/m^3) and GWO (620:0220 mg/m^3). The reduction in NOx shown by WdGWO is 1209.3813 mg/m^3, compared to other algorithms like SRPSO (1245.5730 mg/m^3), GP (1210.2 mg/m^3) and GWO (1271.7679 mg/m^3). Similarly WdGWO shows very good reduction in TSPM 677.2412 mg/m^3 as compared to SRPSO (694.9890 mg/m^3), GP (712.9 mg/m^3) and GWO (712.6989 mg/m^3). The percentage reduction in pollutants by algorithms is calculated as

$$\%\, reduction = \left(\frac{original - obtained}{original} \right) 100$$

Using above equation, the % reduction in SO_2 by WdGWO is calculated as (see the Table 2 for obtained results)

$$\%\text{ SO2 reduction} = \left(\frac{626.4937 - 514.6601}{626.4937} \right) 100$$
$$= 17.8507\ \%$$

Thus the amount of SO_2 is greatly reduced to 17.8507% by WdGWO compared to SRPSO (7.5826%), GWO (1.0330%) and GP (0.0830%). The reduction in NOx is achieved to be 5.1852% by WdGWO compared to GP (5.1210%), SRPSO (2.3478%) and GWO (0.2942%). Similarly the amount of TSPM is reduced to 5.2491 % by WdGWO compared to SRPSO (2.7661%), GWO (0.2884%) and GP (0.2602%).

The last row in Table 2 shows the total pollutants. This row shows the combined reduction by different algorithms. From the table it is clear that WdGWO shows more reduction (2401.2826 mg/m^3). The amount of combined pollutant reduction is 8.2350% by WdGWO compared to SRPSO (3.7154%), GP (2.5872%) and GWO (0.4695%).

The extra ordinary result of WdGWO is seen on reduction of pollutants compared to other counterparts. These results are mainly due to the weighted distances that are incorporated in the basic GWO. In basic GWO, the distances among the wolves are calculated as simple and linear average, that may be misguiding and the whole pack may get trapped in local minima. Thus the proposed WdGWO which is a variant of GWO has shown remarkably enhanced results compared to GWO.

CONCLUSION

This paper presents an application of Weighted distance Grey Wolf Optimizer WdGWO on Delhi Thermal Power Plant TPP. The WdGWO is one of the Nature Inspired (NI) algorithms that has well proved on standard benchmark optimization problems. The rapidly growing society needs the sustained generation of electricity. The major sources of electricity are the TPPs, which generates electricity by burning fossil fuels. The burning of fossil fuels causes air pollution and has major environmental and human health hazard. The poisonous pollutant may be brought down by making use of non-conventional energy sources and by installation of new efficient TPPs; unfortunately the former is in its infancy and later is non-feasible. Thus finding appropriate strategy for existing TPP is only left out option. The major concern in today's world is, to minimize air pollutants and increase the power generation. There are many mathematical techniques to model optimization of air pollution. Since such models turns out to be nonlinear, complex and multimodal, hence most of the classical optimization methods fail to give appropriate solution. This paper first proposes a constraints based mathematical model of Delhi TPPs, then integrate a well-known variant of NI algorithm namely WdGWO. The proposed model and the integration turn out to be fruitful in reducing the amount of pollutants generated by TPPs. The applied WdGWO algorithm brings down the air pollution to a considerably larger extent.

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