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Reducecarbon Emission and Economic Cost in Thermal Power Plant Usinggreen Sigma Steps in Different Optimization Techniques and Compare Their Results to Determine Best Optimal Solution

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Abstract: The thermal power plant production assumes supreme significance in the domain of the electric power utility systems. The social and ecological conditions are adversely impacted by the atmospheric contamination triggered in the course of the production of electricity from the fossil fuels. The steps such as the definition, measurement, analysis, optimization and control performance, all of it plays a pivotal part in the green sigma procedure for organization accomplishment and optimization. The fundamental objective of the paper is to integrate the steps of green sigma into a new global optimization method namely social spider optimization method and compare the results with other techniques in order to determine the best optimal capacity for three and six generator system. In green sigma, the procedure constraints include the power demand related to the generator rating and the carbon footprints of the thermal plant. The optimizations algorithms employed in this paper to minimize the carbon footprint are the Grey Wolf Optimization (GWO) and Social Spider Optimization (SSO) along with the Particle Swarm Optimization (PSO), Cuckoo Search (CS) and the Artificial Bee Colony (ABC) optimization technique. The SSO algorithm is based on the simulation of cooperative behaviour of social spiders and GWO algorithm is based on the hunting mechanism and leadership hierarchy of grey wolves. In the three generator system, the percentage evaluation of reduction between the SSO and the other techniques such as the Conventional method, PSO, CS, ABC and the GWO are 23.69%, 0.9298%, 3.2942%, 0.3814% and 0.5082% respectively. Also in the six generators the reduction between the SSO and other techniques such as the Conventional method, PSO, CS, ABC and the GWO are 4.09%, 2.135%, 3.613%, 0.674% and 0.518% respectively. This statistics confirm the fact that theperformance of Social Spider Optimization (SSO) is better thanother algorithms involved in the evaluation process. The proposed methods have been simulated in the working platform of the MATLAB.

Key words: Thermal Power Plant · Green Sigma · Carbon Emission · Generators and Social Spider Optimization (SSO)

INTRODUCTION

Global warming is posing a big danger to human existence and its impact is seen and felt by all living forms. The concept of Green Sigma was introduced by IBM to combat the environmental challenges arising due to concentration of Greenhouse gases. It provides necessary robust analysis tools to identify solve and achieve environmental sustainability. The pollutants such as NO_x and SO_2, two traditional air poisons and CO_2, a primary greenhouse gas (GHG), are co-generated from burning of fossil fuels, hence their emissions are closely connected [1]. Thermal power generation is a process in which the thermal energy generated by the combustion of coal, oil, gas and other fuels is converted into electric energy by power generation units [2]. The growth in carbon emissions is largely from industry, transport and energy supply, while residential and commercial buildings, forestry/deforestation and agricultural sectors also contribute substantial quantities of carbon dioxide, methane and other greenhouse gases [3]. CO_2 is separated from the flue gas from any source and then transported and used in other processes or stored in a safe place, such as underground storage and ocean storage. To reduce CO_2 emissions, a number of carbon capture and storage (CCS) technologies are available [4].

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Although renewable and sustainable energy can significantly contribute to reduce CO_2emissions, it will take a very long time for them to be easily exploited and widely used. Therefore, fossil fuels will continue to be used because they are relatively abundant and economical [5]. In any case, paying little heed to the justification for looking to enhance green notorieties, measuring a company's addition from enhancing its environmental reputation can be testing. A few analysts have attempted to quantify sways on ecological notoriety by inspecting changes in stock trade offer costs/qualities relating to corporate environmental disclosures [6]. Emission mitigation and thermal power plant (TPP) efficiency improvement are particularly important projects in terms of reducing climate changes [7]. Many companies have shown interest in developing this concept in order to reduce the need for lengthy permitting applications that are needed for conventional land based power plants [8]. Reducing carbon dioxide emissions caused by electricity generation is a driving motivation for increased wind power and other renewable energy installations [9]. The fossil fuels will remain the backbone of the power sector at least in mid-term scenario but viable solutions to significantly reduce the CO_2 emissions need to be developed and deployed in large scale applications for transition to low carbon economy [10]. Proponents of energy efficiency have extensively researched the effects of heat rates on CO_2 emission rates, but, in doing so, they have assumed that plants' output will remain constant [11]. Some of the control strategies are increasing power plant efficiency by making modifications in the existing system, fuel balancing, fuel switching, washing of flue gases and using renewable energy sources [12]. A comparison of urbanization, economy and carbon emissions across various regions and scales reveals a strong urgency of tackling GHG emissions in the developing world [13]. CO_2 emissions from coal-fired thermal power will greatly influence the successful achievement of China's CO_2 emissions reduction target and the investigation of China's coal-fired thermal power development will be of particular benefit as they want to be leaders of low carbon economy [14]. The low-carbon emission developments of electric power system is gaining significance. Some strategies to reduce the emissions form thermal power systems with carbon capture system technology have been proposed and discussed [15]. Release of carbon dioxide into the atmosphere is considered by the IPCC to be one of the main factors causing global climate change. As such, there is a worldwide political effort to reduce CO_2 emissions [16]. A higher ratio of coal consumption in a plant results in a lower environmental efficiency. Compared to the central region, the power plants located in the western region have both lower environmental efficiencies and a lower shadow price, whereas those in the eastern region only exhibit a higher environmental efficiency [17]. These days, the Greenhouse effect has pulled in according to the specialists and the carbon emanation abatement has turned out to be totally crucial. Consequently, generally, the tainting of the climate activated by the releases from the warm power plants has offered a few difficulties to the force utilities and groups [18]. Social-Spider Optimization, which considers both male andfemale spiders as well as their cooperative behaviour forsolving optimization tasks [19]. At the point when noteworthy natural perspectives are identified with GHG emissions just, a point of eco design would be a reduction in the GHG emissions of an item over its whole life cycle. In green sigma appraisal the optimize process is used to reduce the carbon emission and control the elements with points of confinement and distinguished in optimization stage [20].

Literature Review: In 2015, Katherine Hornafius *et al.* [21] had proposed the CO_2 that is created in the fermentation process in an ethanol plant is geologically stored by an enhanced oil recovery (EOR) project. The oil produced from a CO_2-EOR sequestration project is therefore either carbon neutral or carbon negative if the $CO_2$is sourced from the fermentation emissions from an ethanol plant. The 40.3 million metric tonnes of CO_2 fermentation emissions vented during the production of 53.4 million liters of ethanol per year in the U.S. could result in production of 40-100 million barrels of carbon negative oil annually. Utilization of biofuels fermentation emissions worldwide in bio-CO_2-EOR sequestration projects would help achieve global CO_2emission reduction goals.

In 2015, Yatin Sharma *et al.* [22] had proposed automatic generation control (AGC) of a three area thermal system incorporating solar thermal power plant (STPP) in one of the area. The performances of integral (I), proportional plus integral (PI) and proportional plus integral plus derivative (PID) controller are evaluated in the system with and without incorporating STPP. A new computational evolutionary technique called grey wolf optimizer algorithm (GWO) is used for the optimization of secondary controller gains for first time in AGC. Sensitivity analysis reveals that GWO optimized PID controller gains obtained in nominal conditions and parameters are healthy and not necessary to reset for large change in system conditions and parameters.

In 2014 andric *et al.* [23] had proposed to reduce the emission of greenhouse gasses; developed countries tend to increase the use of environmentally friendly renewable energy sources. These environmentally accounting approaches were chosen to determine the maximum supply distance of biomass that allows the co-firing of coal and biomass to be more environmentally efficient than the pure coal combustion. Two methods are used to cover all significant aspects of electricity production process that may influence the environment: carbon footprint and energy evaluation. The addition of approximately 20% biomass to the mass of the combustion mixture causes the decrease in carbon-dioxide emissions for nearly 11-25% and total energy flow for 8-15%. Further the energy loading ratio of co-firing was lower than for the pure coal firing.

In 2013, James *et al.* [24] had anticipated the Social Spider Optimization Algorithm (SSO) to solve global optimization problems. The framework essentially stands on foraging strategy of social spiders, which employs the vibrations spread over the spider web to establish the position of preys. SSO has greater concert compared with other metaheuristics, together with evolutionary algorithms and swarm intelligence algorithms. The concert of SSO is stupendous in contrast with listed algorithms in all three dissimilar groups of functions including unimodal, multimodal and shifted-rotated multimodal optimization problems.

In 2013, Erik Cuevas *et al.* [25] had anticipated a swarm algorithm called the Social Spider Optimization (SSO) for decipher optimization tasks. The SSO algorithm is based on the simulation of cooperative performance of social-spiders. In this algorithm, individuals emulate a group of spiders which interrelate to each other based on the biological laws of the cooperative colony. The algorithm deems two different search agents (spiders): males and females. Depending on gender, each individual is demeanour by a set of dissimilar evolutionary operators which mimic dissimilar cooperative behaviours that are typically found in the colony. The association examines several standard benchmark functions that are normally considered within the literature of evolutionary algorithms.

In 2013 HyoSeon Park *et al.* [26] proficiently suggested the function of a building account for a greater part of the total CO_2 emissions. With a view to cutback the life-cycle energy utilization of a building, the energy used up from both materials in the building stage and from the conduct of the building have to be significantly decreased. An optimal design technique for composite columns in mega edifices employing a genetic approach is envisaged to bring down the expenses and CO_2 emissions from the structural materials in the building stage. The novel optimal approach is performed on a realistic 35-storeyed edifice and the efficient application of structural materials for the sustainable plan of composite columns is intensively explored.

Proposed Methodology: The target of the present investigation is devoted to the design of an innovative model for the power production in the generator by means of the optimization function. The production limit of the individual generators is arbitrarily generated as the initial solutions. It is followed by the evaluation of the fitness function for the individual generators releasing carbon and it has to be guaranteed that the sum of total carbon released by all the generators must be within that of the conservative technique. The investigation is concerned with two cases, the first one based on the three power generators and the second based on the six power generators. The ultimate goal of successfully addressing the economic dispatch issue in the electric power system is invested in ascertaining the production levels together with the minimization of the discharge level using the novel technique in relation to the conventional technique. The innovative technique concatenates with the optimization methods to arrive at the solution for the optimal economic dispatch issue together with the minimization of the carbon decrease. The underlying aim behind the novel method is to integrate the optimization methods like the social spider optimization and the Grey Wolf optimization with the ABC, PSO and the CS procedure and seek to estimate the efficiency of the carbon decrease with the help of the relative soft computing method. The whole procedure is integrated with the optimization approaches coming under the platform of the green sigma. The Green sigma encompasses five key components like the defining, metering, analysis, optimization and control performance and these procedures are integrated with the innovative technique and the contrasted with the optimization approach to illustrate the superiority of the green sigma theory.

Table 1: Pseudo code for social spider incorporate in carbon foot print reduction

Step 1: Initialization
Step 2: Fitness computation (F_i)
Step 3:Based on fitness update the New Spider population
{
Find the number of female and male spiders (V_f and V_m)
Evaluate the weight (w_i) based on the fitness (F_i)
Fitness based initializes the population ($f^0_{i,j}$ and $m^0_{k,j}$
Find the Cooperative operator
Female cooperative operator (f_i^{k+1})
Male cooperative operator (m_i^{k+1})
Mating process find the probability (p_{Ri})
Find the fitness for the new Spider solution
}
Step 5: Store the best spider of the solution so for attained
Stop until optimal solution ($F_{optimal}$) attained
Iteration=Iteration+1
Step 7: Find the error value ( )

Defining: The initial process in the green sigma process is to define all set of variables and constrains utilized in this process in order to reduce the carbon foot prints.

$$IS_{ij} = P_{\min} < P_j < P_{\max} \tag{1}$$

Here, $P_{\min}$ and $P_{\max}$ are the minimum and maximum range of the generator's power ratings whose values are indicated in the below mentioned Tables 2 and 3 for three generator and six generator system respectively. The emission coefficient values are also included in below-mentioned Tables. The Quadratic function incorporated to reveal the emission production in the power plant generators is given by the Equation 2 given below:

$$E_j\,(P_j) = d_j\,(P_j)^2 + e_j\,(P_j) + f_j \text{ Kg/hr} \tag{2}$$

where, d_j, e_j and f_j are the emission coefficients for the unit generator 'j'

Table 2: Emission coefficients and power limits for three generators system

Generator	d_i	e_i	f_i	P_{min}	P_{max}
1	0.0126	-1.355	22.983	20	200
2	0.01375	-1.249	137.370	15	150
3	0.00765	-0.805	363.704	18	180

Table 3: Emission coefficients and power limits for six generators system

Generator	d_i	e_i	f_i	P_{min}	P_{max}
1	0.0042	0.3300	13.86	10	125
2	0.0042	0.3300	13.86	10	150
3	0.0068	-0.5455	40.26	35	225
4	0.0068	-0.5455	40.26	35	210
5	0.0046	-0.5112	42.92	130	325
6	0.0046	-0.5112	42.96	125	315

Metering: In this process the emission control performance is carried out for each individual generator unit *j,* the constraint behind the process is given by below equation:

$$P_{Demand} = \sum_{k=1}^{NG} E_j\,(P_j) \tag{3}$$

Equation (3) states that the demand combined with the unit power generation should satisfy the power demand and at the same time the revealed emission should be at minimal level. Equation (3) is utilized as the fitness function in the optimization algorithms.

The two steps detailed above correspond to the steps of green sigma synchronizing with the preliminary couple of processes in the optimization techniques. The following section elaborates the procedure related to the innovative optimization technique.

Analysis and Optimization

Social Spider Optimization (SSO): The SSO invariably presume that the entire search space represents a communal web, where all the social-spiders interact with one another. In thisapproach, each and every solution in the search space is characterized by a spider location in the communal web. Each spider is given a weight in accordance with the fitness value and two search agents are involved-males and females. The communication is enabled through vibrations on the web and mating produces a new individual or solution. The approach for the SSO process is illustrated by the captioned Pseudo code.

Initialization: The Initial solution (IS_{ij}) is generated randomly by Equation (1) and is utilized as initial solution by satisfying constraint condition given by Equation (4).

$$P_{Demand} = \sum_{k=1}^{NG} (P_j) \tag{4}$$

Here, the concept comprises two cases such as (i) three generators and (ii) six generators where the Number of generators (NG) varies on the basis of the given power demand. If the demand lies between 200 and 400 then the NG is deemed to be three whereas if the given power demand exceeds the defined limit then the NG value is deemed to be six.

Fitness Function: The Fitness computation is the process, which utilizes Equation (3) to find the fitness for the individual solution and this process is evolved as follows.

$$F_i = \min(\sum_{k=1}^{NG} E_j(P_j)) \quad (5)$$

The Minimum of fitness is considered to be best fitness and the fitness corresponding to the solution is said to be optimal power generator rating for the given power demand.

New Population Updation: The novel technique envisages two diverse search agents (spiders) such as the males and females. In accordance with the gender, each and every individual is performed by a set of diverse evolutionary operators which imitate the various cooperative trends which are habitually presumed inside the colony. Taking V as the total number of n-dimensional colony members, the number of male V_m and females V_f spiders in the total populationSisdefined.

$$V_f = floor[03.9 - rand.025).V] \text{ and } V_m = V - V_f \quad (3)$$

where rand is a random number between [0, 1] and floor (.) maps a real number to an integer number.

Weight Assignation: In the biological metaphor, the spider size represents the unique feature which estimates the individual skills to efficiently carry out its delegated functions. Each and every individual (spider) is allocated a weight w_i which characterizes the solution quality which is related to the spider i (regardless of the gender) of the population R. The weight of each and every spider of R is evaluated by means of Equation (4).

$$w_i = \frac{F(R_i) - worst_R}{best_R - worst_R} \quad (4)$$

where $F(R_i)$ is the fitness value obtained by the evaluation of the spider position R_i with regard to the objective function F. The values $worst_R$ and $best_R$ are calculated using below equation.

$$best_R = \min_{k=\{1,2,...N\}} (F(R_k)) and \qquad worst_R = \max_{k=\{1,2,...N\}} (F(R_k)) \quad (5)$$

Initialize the Population Based on Fitness: The algorithm begins by initializing the set S of V spider positions each spider position f_i and m_i is a dimensional vector containing the parameter values to be optimized. Such values are randomly and uniformly distributed between the pre specified lower initial parameter bound p_j^{low} and the upper initial parameter bound pj^{high} given by using equation(6) and (7).

$$f_{i,j}^0 = p_j^{low} + rand(0,1).(p_j^{high} - p_j^{low}) \; (i = 1,2...V_m, j = 1,2,..n) \quad (6)$$

$$m_{k,j}^0 = p_j^{low} + rand(0,1).(p_j^{high} - p_j^{low}) \; (k = 1,2...V_m, j = 1,2,..n) \quad (7)$$

where i, j and k are the parameter and individual indexes respectively, whereas zero signals the initial population hence $f_{i,j}$ is the j_{th} parameter of the i_{th} female spider position.

Cooperative Operators

Female Cooperative Operator: The female spiders bring in a charm or disgust over others irrespective of the sexual orientation. In the case of a specified female spider, the corresponding charm or disgust is habitually generated over the other spiders as evidenced by their vibrations which are released over the communal web. As these vibrations invariably depend on the weight and distance of the members which have instigated them, sturdy tremors are generated by the giant spiders or the neighbouring members which are situated near the person observing them. The former case is concerned with the transformation with respect to the closest member to i which possesses a greater weight and generates the vibration $Vibc_i$. The latter case involves the modification with regard to the best individual of the whole population R which produces the vibration $Vibb_i$. The female vibration $Vibc_i$ and $Vibb_i$ are estimated by means of Equation 8.

$$Vibc_i = w_c.e^{-d_{i,c}^2} \;\; Vibb_i = w_b.e^{-d_{i,b}^2} \quad (8)$$

The Vibration $Vibc_i$ is perceived by the individual $i(R_i)$ as a result of the information transmitted by the member $c(R_c)$ who is an individual that has two important characteristics: it is the nearest member to i and possesses a higher weight in comparison to $I(w_c > w_i)$. The Vibration $Vibb_i$ are perceived by the individual i as a result of the information transmitted by the member $b(R_b)$ with b being the individual holding the best weight that aids fitness of the entire population R such that $w_b = \max_{k\epsilon\{1,2,...N\}} w(k)$.

If rm is smaller than threshold power factor (PF) an attraction movement is generated; otherwise a repulsion movement is produced. Therefore, such operator can be modelled as follows:

$$f_i^{k+1} = \begin{cases} f_i^k + \alpha.Vibc_i.(R_c - f_i^k) + \beta.Vibb_i.(R_b - f_i^k) + \delta.(rand - \frac{1}{2}) \text{ with } \quad proability\, PF \\ f_i^k - \alpha.Vibc_i.(R_c - f_i^k) + \beta.Vibb_i.(R_b - f_i^k) + \delta.(rand - \frac{1}{2}) \text{ with } \quad proability\, 1 - PF \end{cases} \tag{9}$$

where α,β,δ and *rand* are random numbers between [0, 1] whereas k represents the iteration number. The individual R_c and R_b represent the nearest member to *i* that holds a higher weight and the best individual of the entire population *R*.

Male Cooperative Operator: Male members possessing a weight value greater the median value within the male population, are deemed as the dominant individuals *D*. Conversely, those within the median value are considered as the non-dominant *ND* males. With the intention of performing the corresponding9 evaluation, the male population $M(M = \{m_1, m_2 ... m_{Nm}\})$ is orchestrated in accordance with their weight value in the descending order. Hence, the individual having weight w_{Vf+m} situated in the middle is taken as the median male member and the vibration of the male $Vibf_i$ evaluated with the help of Equation 10 given below. The Vibration $Vibf_i$ observed by the individual $i(R_i)$ on account of the data communicated by the member $f(R_f)$ with *f* being the closest female individual to *i*.

$$Vibf_i = w_f . e^{-d_{i,f}^2} \tag{10}$$

Since indexes of the male population *M* in regard to the entire population *R* are increased by the number of female members V_f, the median weight is indexed by V_{f+m}. According to this, change of positions for the male spider can be modelled as follows.

$$m_i^{k+1} = \begin{cases} m_i^k + \alpha.Vibf_i.(R_f - m_i^k) + \delta.(rand - \frac{1}{2}) \, if \quad w_{V_{f+i}} > w_{V_{f+m}} \\ m_i^k + \alpha.\left(\dfrac{\sum_{h=1}^{V_m} m_h^k . w_{V_{f+h}}}{\sum_{h=1}^{V_m} w_{V_{f+h}}} - m_i^k \right) if \quad w_{V_{f+i}} \le w_{V_{f+m}} \end{cases} \tag{11}$$

where the individual R_f represents the nearest female individual to the male member *i* where as;

$$\left(\sum_{h=1}^{V_m} m_h^k . w_{V_{f+h}} \Big/ \sum_{h=1}^{V_m} w_{V_{f+h}} \right)$$

Correspond to the weighted mean of the male population *M*.

By employing the above-mentioned operator, two diverse phenomena are generated. In the former, the set *D* of particles is fascinated to others with the intention of inciting the act of mating, which has the effect of permitting the integration of the diversity into the population. In the latter, the set *ND* of particles is fascinated to the weighted mean of the male population *M* and this phenomenon is effectively employed to moderately regulate the search procedure in accordance with the average performance of a subgroup of the population.

Mating Process: The Mating in a social-spider colony is carried out by the leading males and the female members. In such a scenario, when a leading male m_g spider ($g \in D$) finds a set E^g of female members within a specified range r(which is considered as the range of mating), it mates, producing a new brood R_{new} which is produced taking due account of the entire elements of the set T^g which, in turn, has been created by the union $E^g \cup m_g$. It is pertinent to note that if the set E^g is vacant, the mating function has to be abandoned. The range *r* is concisely described as the radius which is dependent on the dimension of the search space. Now the female ($F = \{f_1, f_2, .. f_{Vf}\}$) and male ($M = \{m_1, m_2, ... m_{Vm}\}$) are randomly initialized where $R = \{R_1 = f_1\ R_2 = f_2 ...... R_{Vf} = f_{Vf}, R_{vf+1} = m_1, R_{vf+2} = m_2\ R_V = m_{Vm}\}$ and the radius mating is calculated.

$$r = \frac{\sum_{j=1}^{n} (p_j^{high} - p_j^{low})}{2.n} \tag{12}$$

In the mating process, the weight of each involved spider (elements of T^g) defines the probability of influence for each individual into the new brood. The spiders holding a heavier weight are more likely to influence the new product, while elements with lighter weight have a lower probability. The influence probability P_{Ri} of each member is assigned by the roulette method, which is defined as follows;

$$p_{Ri} = \frac{w_i}{\sum_{j \in T^k} w_j} \text{ where } \ i \in T^g \tag{13}$$

When the new spider is generated, it is contrasted with the new spider candidate R_{new} having the worst spider R_{wo} of the colony, depending on their weight values. If the new spider is superior to the worst spider, the worst spider is substituted by the new one. If not, the new spider is eliminated and the population does not undergo any modifications. On the contrary, in the case of substitution, the new spider takes control of the gender and index from the substituted spider, thus ensuring that the whole population R preserves the original rate between female and male members.

RESULTS AND DISCUSSION

The proposed system works for two different cases, one based on the three power generator and the second one based on six power generators. Here the Social Spider Optimization algorithm (SSO) performance is better than those of the other algorithms. The SSO algorithm performance is compared with the those of the Conventional, Grey wolf optimization algorithm (GWO), Cuckoo Search (CS), Particle Swarm Optimization (PSO), Artificial Bee Colony Optimization (ABC) and the comparative evaluation revealed that Social Spider Optimization (SSO) algorithms has better prospects in handling the load dispatch problem and evolve optimal solutions satisfying the emission and generator capacity constraints.

Table 4 shows the carbon emission under variable load for the three generator system. The power demand ranges from 200-400 MW with a span of 50 MW each for Conventional, PSO, CS, ABC, GWO and SSO. The percentage reduction achieved in the SSO is0.30%, 0.11%, 0.622%, 0.704% and 0.1604% as compared with conventional technique. Thus, the computation results show that SSO has generated the best-optimized solution when compared to other techniques.

Figure 1 below shows the percentage deviation of all the optimization algorithms such as the Conventional, PSO, CS, ABC and GWO techniques from SSO method. In the three generator system the percentage deviation achieved under conventional method from SSO are 15.83%, 21.06%, 25.59%, 27.5% and 28.5%. The corresponding figures for the PSO from the SSO are 0.43%, 0.556%, 1.248%, 0.966% and 1.449%. The relative figures for the CS from the SSO are 2.598%, 5.79%, 3.206%, 0.966% and 3.911%. The relative figures for the ABC from the SSO are 0.303%, 0.117%, 0.622%, 0.704% and 0.160%. At last, in the case of the GWO from SSO the percentage deviation is 0.467%, 0.611%, 0.795%, 0.33% and 0.338%. Thus the graph depicts the fact that the nearest algorithm of the SSO is found to be the ABC optimization algorithm.

Table 5 and Figure 2 shown below illustrates the functioning of the six power generator system. The carbon emission under variable load for the six generator system is shown in Table 5. Here the power demand ranges from 500-1100 MW with a span of 100 MW each for the different techniques such as the Conventional, PSO, CS, ABC, GWO and SSO techniques. The reduction achieved in the SSO are 0.651%, 1.067%, 0.291%, 1.050%, 0.686%, 0.583% and 0.39% when compared with ABC. Thus, the evaluation results make it clear that proposed SSO technique has generated the best enhanced solutions when compared to the other techniques.

Figure 2 shows the percentage variation for all the optimization algorithms such as the Conventional, PSO, CS, ABC and GWO. In the six generator system the percentage deviation effected under the conventional method from the SSO are 1.55%, 4.02%, 3.23%, 4.04%, 5.57%, 5.191% and 5.07%. The corresponding variation of the PSO from the SSO are 6.37%, 3.215%, 0.817%, 1.050%, 1.336%, 0.857% and 1.303%. The variation of the CS from the SSO are 10.36%, 3.597%, 1.106%, 1.050%, 4.813%, 2.539% and 1.831%. In the case of the ABC variation from the SSO are 0.651%, 1.067%, 0.291%, 1.050%, 0.686%, 0.583% and 0.39%. Further, the percentage variation of the GWO from the SSO is 0.42%, 0.807%, 0.482%, 0.357%, 0.549%, 0.700% and 0.312%. This leads us to conclude that the closest algorithm of the SSO is found to be the ABC optimization algorithm.

The above Figure 3 shows the Carbon Emission obtained for various iterations of the PSO, CS, ABC, GWO and the SSO for the 300 MW power demand. The values are estimated for every 10 iterations from 1-100 and applied for each algorithm.

The Figure 4 shows the Carbon Emission obtained for various iterations of the Conventional, PSO, CS, ABC, GWO and the SSO for the 600 MW power demand. Here also the values are estimated for every 10 iterations from 1-100 and applied for each technique. Thus, the economic dispatch problem in the electric power system is solved by minimizing the emission level of the system using a method which demonstrates high performance.

Table 4: Carbon emission under variable load for three generators system

Power demand (MW)	Conventional	PSO	CS	ABC	GWO	SSO
200	529.26	447.3847	457.3364	446.8093	447.545	445.454
250	597.499	474.2944	500.6522	472.2116	474.56	471.656
300	684.826	516	526.44	512.75	513.646	509.56
350	791.24	579.2368	579.2368	577.709	575.54	573.64
400	916.742	664.9562	681.9939	656.3968	657.546	655.32

Table 5: Carbon emission under variable load for six generators system

Power demand (MW)	Conventional	PSO	CS	ABC	GWO	SSO
500	261.634	275.0969	287.3355	259.2496	258.65	257.56
600	338.992	336.1699	337.5002	328.8721	328.01	325.36
700	434.38	423.7861	425.0213	421.5496	422.356	420.32
800	547.796	531.234	531.234	529.2357	527.54	525.654
900	679.24	650.0425	673.7841	645.7846	644.9	641.354
1000	828.72	792.4867	806.1682	790.3046	791.235	785.694
1100	996.224	958.1743	963.3274	949.3912	948.65	945.685

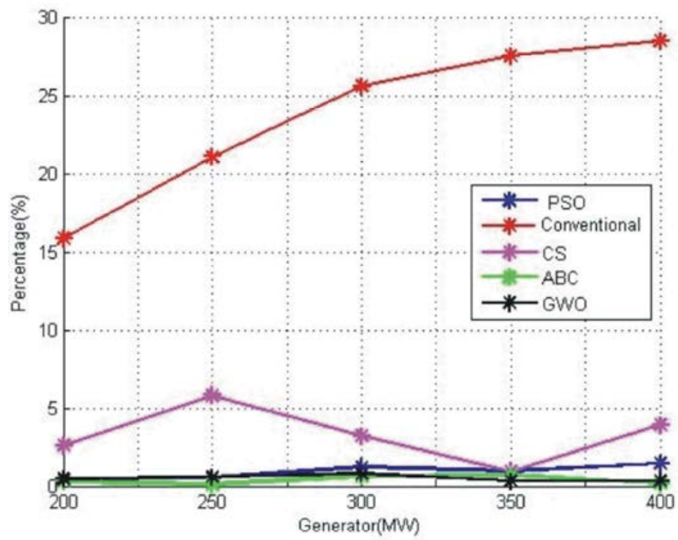

Fig. 1: Deviation between each optimization techniques from SSO for three generators system

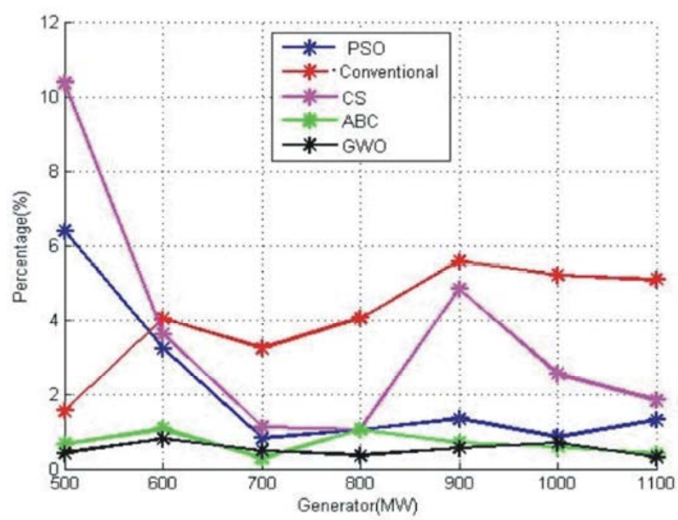

Fig. 2: Deviation between each optimization techniques from SSO for six generators system

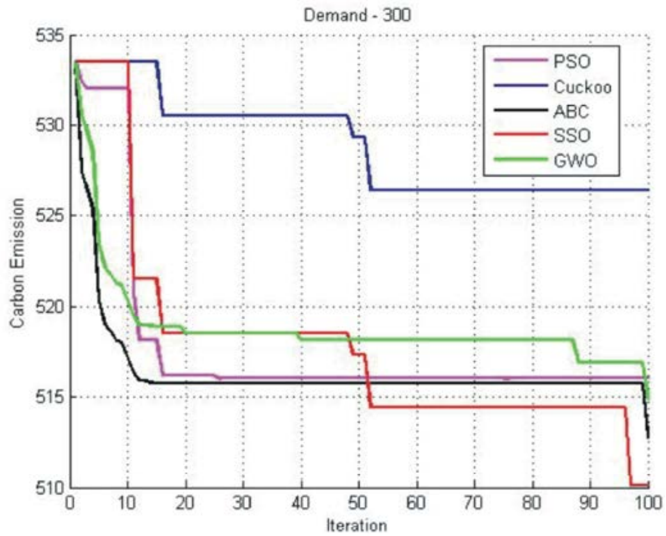

Fig. 3: Carbon Emission obtained for various iterations of PSO, CS, ABC, GWO and SSO for 300MW power demand

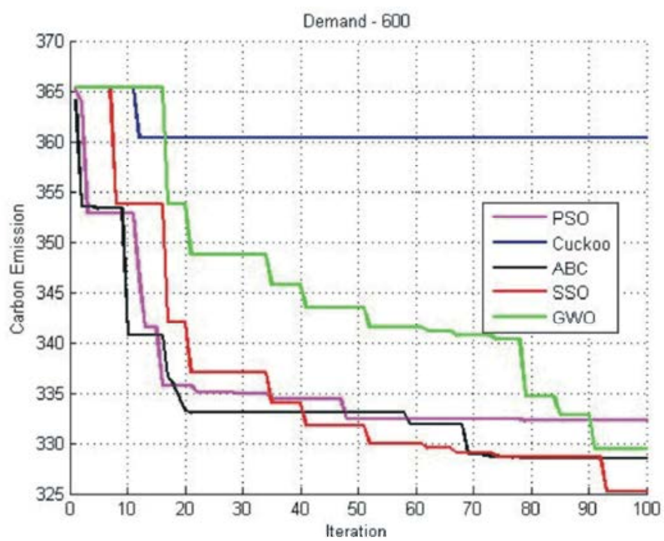

Fig. 4: Carbon Emission obtained for various iteration of PSO, CS, ABC, GWO and SSO for 600 MW power demand

CONCLUSION

Time and again it has been proved by many researchers that major contributing factors for carbon emissions are from thermal power plants.In this paper, we have discussed the compatibility of applying different optimization techniques to reduce the carbon footprint of thermal plant based on different power demands such as 200 to 400MW for the three generator and 500 to 1100MW for the six generator systems. The green sigma approach helps us to identify the core issues to be addressed and helps to prioritize them, collect relevant data of the problem under consideration, provide right tools to analyse and optimize the data to derive the best solution which accomplishes the objective and sustain environmental benefits. Metaheuristics based on evolutionary computation and swarm intelligence are examples of nature inspired techniques to solve complex problems. The shortcomings such as premature convergence and local minima are overcome in SSO method and comparative evaluation of results proves its superiority over other algorithms. The Social Spider Optimization algorithm (SSO) is utilized for the three generator system and the rate of carbon emission varies at the rate of 3.17% in each power demand. And for the six generator system the rate of carbon emission varies at the rate of 1.02% in each power demand. Thus it is recommended to employ SSO method to solve Economic load dispatch problem in power plants. Further research can be done using advanced optimization techniques and results may be compared to identify high performance algorithm.

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