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Research paper

Optimizing Generating Unit Scheduling for Emission Reduction in Thermal Power Stations with Integrated Solar Energy Systems

Mihirkumar C. Rathod [1] *, Sanjay R. Vyas [2]

[1] *Research Scholar, Engineering & Technology, Kadi Sarva Vishwavidyalaya, Gujarat, India*
[2] *Department of Electrical Engineering, LDRP Institute of Technology & Research, Gujarat, India*
**Corresponding author E-mail: mrldrp@gmail.com*

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Abstract

Air pollution control from thermal power stations (TPS) is achieved by minimizing flue gases emission. There are many optimization techniques which can be used towards effective emission reduction, but these techniques may often require additional arrangement or devices. This study presents an alternative approach to emissions minimization by scheduling generating units in a strategic manner without the need to add extra equipment. Increasingly expensive fossil fuels and the improving technology for renewable energy can be picked up by solar energy systems to reduce emissions. In this paper, the question of generating unit schedule for a TPS with integrated solar energy (SE) systems in order to reduce emissions is addressed. Thus, load dispatch scheduling associated with solar energy can decrease overall emissions with the same power output. The schedule is optimized to account for uncertainties to manage the challenge of predicting real power consumption to improve emission reduction under changing conditions. In the study, reduction of NOx, SO2, and CO2 emissions is evaluated using evolutionary programming. Results show that by adding solar energy systems into the mix, better emission reductions can be achieved compared to the conventional TPS systems alone. In particular, there are major reductions in NOx, SO2, and CO2 emissions when solar energy is combined with marginal adjustments in the generation schedule. Furthermore, the approach enables the understanding of cost consequences from generating unit scheduling. All in all, the proposed method makes TPS operations more efficient by improving environmental benefits.

Keywords: *Emission Reduction; Solar Energy Integration; Optimization Scheduling; Evolutionary Programming.*

1. Introduction

A multitude of studies in recent years have centered around improving the understanding and management of emissions from power generation systems, wherein side effects can be quite different depending on type of primary energy and power dispatch strategy. This thesis covers such contributions in the literature related to key research contributions in this field, focused on developing evolving strategies for reducing greenhouse gas (GHG) emissions from thermal power plants and integrating renewable energy sources [18].
On the basis of the perspective of consumer responsibility, put forward a method to calculate the CO2 emission at provincial level in China. With this method that includes the embodied emissions in imported electricity through source specific emission factors, they uncover significant regional disparities with Inner Mongolia exports reducing by 191 Mt and Hebei imports increasing by 75 Mt. They push for incorporating these consumption based emissions within local CO_2 mitigation policies as a way to address the local effects [1]. In life cycle greenhouse gas emissions are compared between natural gas combined cycle (NGCC) and imported coal thermal power plants in India [19]. According to their results, NGCC plants emit 584 g CO_2 eq/kWh and imported coal plants emit 1,127 g CO_2 eq/kWh so that the environmental impact of coal fired power plants is almost twice greater than the natural gas plants. The results of this study indicate that the global warming potential and human health impacts differ greatly between these two energy sources [2]. In view of this suggest a holistic power dispatching system (named collaborative power dispatching system, CPDS) that integrates with carbon emission trading to enhance the efficiency and profitability of regional Chinese biomass power systems [20]. According to their research, carbon trading can minimize emission and optimize power generation by replacing thermal units with biomass units and pumped storage can be used in load management [21]. While carbon trading does not have a significant effect on the CPDS in the short run, the study suggests that growing trading prices or lowering free quotas could encourage more emission reductions and persuade the use of renewable energy sources [3]. This paper is which develops a mathematical model called composite probabilistic energy emissions dispatch (CPEED) for the integration of renewable energy systems by adopting the advanced black widow optimization (ABWO) algorithm [22]. The integration of wind and solar energy into thermal power dispatch significantly decreases fuel costs and pollutants emissions, increases the use of renewables and

diminishes reliance on imported fuels, they study. The results shown here point out that with optimized dispatch strategies it is possible to simultaneously improve both the environmental performance and cost efficiency in power generation [4].

Literature reviewed shows substantial progress in the development of knowledge and emission management for power generation systems. Emission calculation methods innovations, comparison of fuel types, and integration of renewable energy sources complement this approach and allow increasing the effectiveness of the emission reduction of the power generation. Enhanced greenhouse gas emissions reductions and overall sustainability are achieved through incorporating consumer based emissions metrics into a dispatch strategy, in conjunction with the use of carefully designed generic carbon trading mechanisms, as demonstrated [23].

The results of this study offer direct implications to the need to continue working on research and development for improving emission reduction strategies and ushering in the use of cleaner energy sources, especially via the integration of solar, wind and thermal energy from hybrid power systems. The utility of the Backtracking Search Algorithm (BSA) in the ELD problems of the integrated wind, solar, and thermal system with variable renewable resources is shown [5]. In addition develops a scheduling approach combining thermal generators with wind farms and solar PV modules with storage along with uncertainties and minimization of real time adjustments costs using Genetic Algorithms and Monte Carlo Simulation [6]. To mitigate the coverage of solar thermal power generation in terms of economic and environmental challenges, integrate the method with nonlinear simplex techniques [7]. How to improve traditional optimization techniques to optimize multiple objectives in hydrothermal power systems is proposed through the α constrained simplex method (ACSM) to address scheduling problems in the hydrothermal wind solar systems [8]. According to the hybrid sine–cosine algorithm (HSCA) is used to optimize generation scheduling in a dynamic setting while addressing uncertainties [10] and as per there is a debate on an optimal balance in coal and photovoltaic systems by considering the economic and environmental factors [9]. Finally, propose the benefits of the thermal storage in the solar thermal power plant with the increased storage capacity where the storage capacity improves the efficiency and reduces the cost [11]. Overall, these studies highlight the significance of advanced modeling and optimization tactics to promote the integration and efficiency of hybrid solar–wind–thermal energy systems, generating knowledge on the balance of economic, environmental, and operational considerations [25]. In general, optimization of these hybrid systems has advanced greatly as indicated by the reviewed studies. Sophisticated algorithms, especially BSA, Genetic Algorithms, and the αconstrained simplex method, prove capable in the challenge of economic load dispatch and scheduling management. In addition, such hybrid sine–cosine and enhanced thermal storage strategies also show how these technologies can be introduced in a more harmonious way to enhance economic efficiency while promoting environmental and operational aspects. By combining all of these insights, we present an overall strategy to improve renewable energy systems' performance and the integration of these systems with a focus on the overall operational efficiency of renewable energy systems as well as the environmental benefits [24].

The challenge of introducing variable source solar, wind, and thermal energy into a hybrid power system is complex and requires the use of advanced optimization techniques to mitigate the impact on emissions. In this regard, several algorithmic approaches to optimize power generation scheduling such as in hydrothermal, and hybrid systems have achieved great strides [26]. have proposed an evolutionary programming (EP) technique for short term hydro thermal scheduling overcoming the constraints like power balance, water discharge, reservoir volumes, etc. A demonstration on an example system shows that their method is more cost efficient and globally optimal compared to classical gradient search and simulations annealing techniques [12]. Artificial bee colony (ABC) algorithm has been applied for dynamic economic dispatch (DED) problems with units including valve-point effects. In the context of ten- and five unit test systems their study demonstrated the algorithm robustness to generate the optimized power over time within unit and ramp rate constraints. The ability of the ABC algorithm to effectively handle non smooth cost functions was validated through the superiority in the solution quality and computational efficiency [13]. A hybrid approach that combines the artificial fish swarm algorithm (AFSA) with the real coded genetic algorithm (RCGA) is proposed as a combined method for the short term hydrothermal scheduling. This method of utilizing both GSA and PSA for global and local search respectively introduces the RCGA. Global search method performs and effectively solves the BCO problem of fuel cost minimization when compared to other methods in tests on hydrothermal system [14]. Short term hydrothermal scheduling has been advanced by using quasi reflected symbiotic organism's search algorithm. By incorporating quasi-reflected scheme, this standard symbiotic organisms search algorithm is successfully enhanced in optimizing hourly outputs as well as minimizing generation costs as confirmed through comparative analyzes with the other methods [15]. In short, artificial bee colony algorithm for the short term optimal scheduling of hydro thermal power plants was the focus of which reduces the fuel costs and maximizes the hydro resource benefits. Moreover, their approach includes transmission losses and computational speeds and operation costs are faster and cheaper than previous methods [16]. Particle swarm optimization (PSO) for short term scheduling of thermal hydro solar power systems was explored. According to their simulations, PSO best reduces the fuel cost and emission with proper optimization of use of multiple power sources and is superior to other scheduling approaches in terms of system integration and performance [17].

It can be inferred that from the reviewed literature, power generation scheduling has made substantial advancements in optimizing the generation schedules through use of sophisticated algorithms. While all of them have this capability to an extent, evolutionary programming has an edge when it comes to handling complex constraints and improving cost effectiveness in hydrothermal and hybrid systems. Additionally, artificial bee colony methods and hybrid approaches have some advantages, however, evolutionary programming is shown to be far more effective. The particle swarm optimization is also included to increase its capability of accelerating the performance of multi source power systems. Overall, these works highlight that the field of optimization technique is still under evolution and that the evolutionary programming is an extremely useful approach in finding better and more efficient scheduling for power generation with lower cost [27].

Although much effort is made regarding optimizing of power generation scheduling, the gap still remains in simultaneous adopting such algorithms as well as tailored to emission reduction for hybrid solar-thermal power systems. While methods like evolutionary programming are currently known as great methods to handle economic and operational issues, the application of this upon minimization of emission is not well treated in research. Also, although various improvements have been made in thermal storage and in hybrid algorithms to improve efficiency, comprehensive models that investigate both emissions reductions and economic performance are rather limited. This gap must be closed, and integrated optimization strategies featuring reduction of emissions on a range of hybrid power systems are required [28].

2. Methodology

Integrating solar energy in to power systems has complex equity and inequality costs, especially in terms of balancing costs between solar and thermal integrated energy. These challenges can be tackled with evolutionary algorithms (EAs) by their capabilities of optimizing solutions that take both economic impacts and fairness in distribution into account. Due to their capacity to explore a wide range of solutions and evolve effective strategies, EAs are suitable in handling such constraints. Through their commitment, they can make the initial

investment required for solar infrastructure balance out the solar operational costs that they are going to have to pay, and thus, financial impacts can be equally shared. Since solar power generates zero air pollution, EAs can choose to apply the solutions that maximize environmental benefit with least environmental disparity, which is same as reducing the overall emissions most efficiently [14].
Evolutionary algorithm
Evolutionary optimization techniques are advanced optimization technique. Evolutionary optimization methods are based on the theory of population. Use mutation and recombination to improve individual results which already discuss in [15].
After the exhibition, we delved into the evolution of evolutionary programming within the realms of design research and optimization. Initially, Lawrence Fogel pioneered the use of evolutionary programming primarily for the development of end-user machines. Over time, this approach has been refined with the introduction of self-adaptive parameters and various mutation strategies.
Research has demonstrated the effectiveness of classical evolutionary programming in designing economic distributors. The appeal of classical evolutionary programming lies in its simplicity compared to Genetic Algorithms (GA), as it does not require specialized encoding. Instead, it operates directly with real-valued parameters, simplifying the process.
Additionally, evolutionary programming does not impose restrictions or modifications on the objective function, which further simplifies its application to various problems. This ease of integration makes it particularly useful in algorithm development for economic load balancing.
Differential evolution, a related technique, has been successfully applied across several domains. Beyond energy engineering, differential evolution has also found applications in filter design, neural network training, fuzzy logic applications, and optimal control problems. It plays a crucial role in achieving economical load balancing and optimal solutions. Flow Chart for Evolutionary Programming shown in Fig. 1.

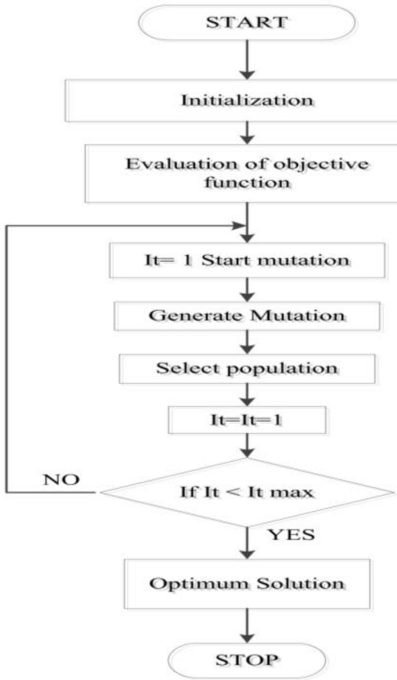

Fig. 1: Flow Chart for Evolutionary Programming.

The algorithm for differential evolution in economic load balancing typically follows these main steps:

- Initialization: Set up initial parameters and population.
- Evaluation: Assess the fitness of each individual.
- Repeat: Continuously refine solutions through iterative processes.
- Mutation: Introduce variations to enhance diversity.
- Crossover: Combine features from different solutions to create new candidates.
- Evaluation: Reassess the fitness of the newly created solutions.
- Selection: Choose the best solutions to move forward.

A flowchart illustrating the optimization process using evolutionary programming is provided for a clearer understanding of these steps.
For the current study, the objective function is defined as follows:
Minimizing NOx emissions

$$F_2 = \sum_{i=1}^{NG} \left(d_{1i} Pg_i^2 + e_{1i} Pg_i + f_{1i} \right) \quad \text{kg/h} \tag{1}$$

Equation (1) Where d1i, e1i, and f1i are NOx emission coefficients.
Minimization of SO_2 Emission

$$F_3 = \sum_{i=1}^{NG} \left(d_{2i} Pg_i^2 + e_{2i} Pg_i + g_{2i} \right) \quad \text{kg/h} \tag{2}$$

Equation (2) Where d2i, e2i and f2i are SO_2 emission coefficients.
Minimization of CO_2 Emission

$$F_4 = \sum_{i=1}^{NG}\left(d_{3i}Pg_i^{\ 2} + e_{3i}Pg_i + f_{3i}\right) \quad \text{kg/h} \tag{3}$$

Equation (3) Where, d3i, e3i and f3i are CO_2 emission coefficients.
Primary constraint:
The generator output is the primary constraint or equality constrain and the equation is in accordance with it is given, The Equation (4) is given as,

$$\sum_{i=1}^{N} Pg_i = P$$

$$\sum_{i=1}^{N} Pg_i = P_D + P_{LOSS} \tag{4}$$

P_D = total load connected to the grid and
P_{LOSS} = total loss in the over system
Secondary constraint:
Secondary constraints or Inequality constraints is defined as maximum and minimum range of sole power station.

$$P_{MIN} \le Pgi \le P_{MAX} \tag{5}$$

The boiler, turbine or generator capacity determines how much power the generating unit can output at its highest level.
Generator limit (inequality constraint)

$$PgiMIN \le Pgi \le PgiMAX \tag{6}$$

Where PgiMIN and PgiMAX are the Minimum and Maximum capacity of generation
Power balance (equality constraint)

$$\sum_{i=1}^{NG} Pg_i - (P_D + P_L) = 0 \tag{7}$$

Where PD is the load demand, PL is the transmission losses.
Where, equality constraint representing power balance and inequality constraint representing unit generating capacity.

3. Result and discussion

The data generated represents the performance metrics of a thermal power station. Sampling was conducted exclusively at power outputs of 220 MW, 220 MW, and 130 MW. The recorded data pertains to the generator's operational parameters and efficiency at these specific output levels. Table 1 provides detailed generation data for the power plant, including various metrics such as output levels, fuel consumption, and operational efficiency at different points in time.

Table 1: Generation Data

Unit No.	Generator (MW)	Maximum (MW)	Minimum (MW)
1	220	250	100
2	220	245	90
3	130	110	30

Table 2: Generation Constant

Unit No.	Ai	Bi	Ci
1	0.00526	8.657	328.24
2	0.00626	10.12	136.31
3	0.00545	9.68	59.46

Table 3: Loss Coefficient for the Given Station

Unit No.	Ai	Bi	Ci
1	0.00525	8.625	328.26
2	0.00636	10.12	136.24
3	0.00512	9.36	59.23

Meanwhile, Table 2 presents the generator constants, which are crucial for understanding the machine's performance characteristics, such as its efficiency and power factor. Table 3 outlines the loss coefficients associated with the plant, which represent the losses incurred in the system due to factors like friction, heat dissipation, and electrical inefficiencies. These tables collectively offer a comprehensive view of the plant's operational and performance parameters.

Table 4: NOx Emission Coefficient for the Station

Unit No.	Hi	Ji	Ki
1	0.006824	0.34851	80.9584
2	0.006425	0.72586	28.8354
3	0.003254	1.34258	324.1245

Table 5: SO_2 Emission Coefficient for the Station

Unit No.	Li	Mi	Ni
1	0.001354	5.05486	51.3365
2	0.002254	3.84471	182.2125
3	0.001362	4.45236	508.5354

Table 6: CO_2 Emission Coefficient for the Station

Unit No.	Ri	Si	Ii
1	0.265254	-61.01657	5080.658
2	0.140036	-29.95354	3824.245
3	0.105587	-9.552247	1342.365

Table 4 details the NOx emission coefficients for the plant, which indicate the amount of nitrogen oxides emitted per unit of energy produced. Table 5 provides information on SO_2 emission coefficients, representing the sulfur dioxide emissions per unit of energy output. Table 6 outlines the CO_2 emission coefficients, showing the carbon dioxide emissions relative to the energy generated. Together, these tables give a complete overview of the plant's emissions performance and environmental impact for nitrogen oxides, sulfur dioxide, and carbon dioxide.

In Case 1, with a total load of 300 MW distributed equally among three power plants, calculate the coal needed for each plant's power generation. Also, determine the emissions of CO_2, SO_2, and NOx associated with this coal consumption.

Table 7 provides emission data for a 300 MW coal-fired power plant, detailing NOx, SO_2, and CO_2 emissions using the evolutionary method. To determine the environmental impact, we compare these emissions with those of an alternative renewable energy source, like wind or solar, which usually have negligible direct emissions. From this comparison, we can identify the best energy solution by selecting the renewable source because it has much less emissions as compared to the coal-fired plants.

Table 7: Result for 10 ITR

Sr. no	PG1 (MW)	PG2 (MW)	PG3 (MW)	Total Gen. (MW)	NOx (kg/h)	SO_2 (kg/h)	CO_2 (kg/h)
1	152.0726	104.7154	45.49856	302.2866	492.1478	2173.048	61489.48
2	151.6932	104.8082	44.87105	301.3725	492.1478	2173.048	61489.48
3	151.6918	104.8087	44.8707	301.3712	491.2902	2168.522	61364.89
4	151.6935	104.8867	44.71498	301.2952	490.2887	2168.515	61364.62
5	151.6739	104.7099	44.47943	300.8633	488.5032	2168.151	61366.78
6	151.6738	104.7037	44.4751	300.8526	487.6265	2166.202	61311.58
7	151.6664	104.7063	44.47774	300.8504	481.6275	2166.154	61310.09
8	151.6741	104.7012	44.47531	300.8506	481.6147	2166.137	61308.97
9	151.6741	104.7012	44.47531	300.8506	481.6262	2166.146	61309.72
10	151.6741	104.7012	44.47531	300.8506	481.6262	2166.146	61309.72

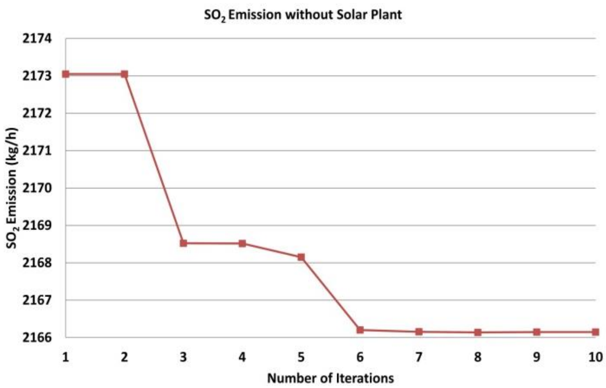

Fig. 2: SO_2 Emission without Solar Plant.

In Fig. 2 NOx emissions vary across many iterations. The figure shows a detailed mapping of concentration of NOx and its fluctuations at all stages of the testing iterations.

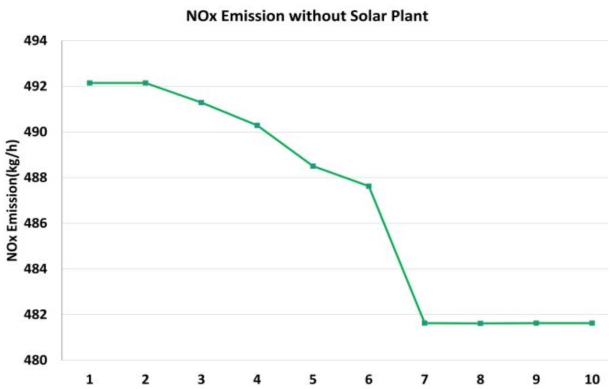

Fig. 3: NOx Emission without Solar Plant.

Fig. 3 shows the sulfur dioxide (SO_2) emissions which is the visualization of the variation of SO_2 per generation from the power plant for different iterations. This figure shows how SO_2 emissions change and become stable over time.

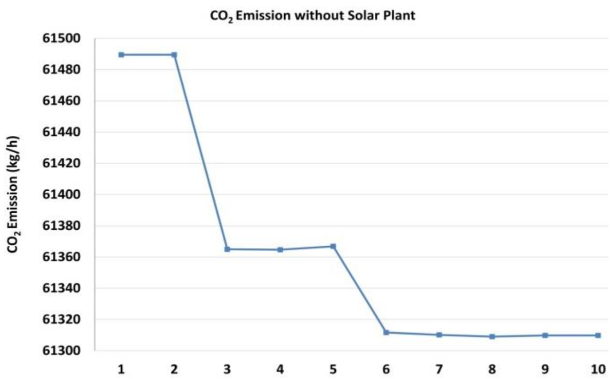

Fig. 4: CO_2 Emission without Solar Plant.

Fig. 4 shows carbon dioxide (CO_2) emissions of power generation and their iterations. According to the data across all figures, note that the decay in emission values reaches steady state after roughly seven iterations. An observation made in the results of this study is that after this point, occasional spikes in reduction of emissions aside, there is a clear pattern in emission reductions, which is indicative of the effective nature of solar power integration, as fuel for continued reduction of emissions is sustained.

Case 2 faces the task of lowering emissions of NOx, SO_2 and CO_2 with the use of renewable energy sources. In particular, evaluation of the implementation of a solar power plant as an alternative to the conventional coal fired power generation is being considered. Solar energy is expected to dramatically decrease emissions of such pollutants since solar power systems essentially generate no direct emissions during operation.

In such a case, the solar power plant will be optimized, to make solar power replacement of coal fired power generation more effective, for aspects of energy output, efficiency or environment. The main optimization process will be the analysis of the system's ability to achieve the required reduction in the emissions and to ensure the reliable power generation.

In addition to that, another advantage associated with incorporating solar energy system is that it operates consuming miniscule costs when compared to fossil fuel based plants. Solar power plants have minimal maintenance requirement and do not have fuel costs, thereby lower the long-term operating cost.

Overall performance and economic benefits of the solar power plant are depicted in the Table 8. The data presented in this table contain the plant's emission reductions, operational efficiency, their associated cost analysis that is made clear in contrast to the coal fired plant. This brings out the advantages of utilizing solar energy, plus how converting will give the masses a better deal environmentally and with spending.

Table 8: Generation Data with Solar Plant

Unit No	Generator rating in MW	Maximum value in MW	Minimum value in MW
1	220	250	100
2	220	245	90
3	130	110	30
4(solar)	25	25	5

Table 9: Loss Coefficient for the Given Plant

Unit No.	Ai	Bi	Ci
1	0.0000146	0.0000164	0.0000175
2	0.0000187	0.0000124	0.0000264
3	0.0000136	0.0000234	0.000163
4(solar)	0.0000019	0.0000022	0.0000024

In the above Table 9, the loss coefficient for each plant has been considered because losses are inherent in power generation processes. This means that the actual energy output of the plants is reduced by these losses, impacting overall efficiency.

Tables 4, 5, and 6 present the emission coefficients for NOx, SO_2, and CO_2, respectively, for each type of power plant. These tables show the amount of each pollutant emitted per unit of electricity generated. In contrast, the solar power plant is represented with a zero emission coefficient for all these pollutants. This is due to the fact that solar power generation does not produce any direct emissions during operation, highlighting a significant environmental advantage of using solar energy. The absence of emissions from solar power plants underscores their role as a cleaner and more sustainable energy source compared to traditional fossil fuel-based plants.

Table 10: Result for 10 ITR with Solar Power Plant

Sr. no	PG1 (MW)	PG2 (MW)	PG 3 (MW)	PS 1(MW)	Total Gen (MW)	Emissions Nox (kg/h)	SO_2 (kg/h)	CO_2 (kg/h)
1	141.073	102.713	41.498	17	302.2844	467.7702	2065.41	58443.71
2	141.122	102.835	41.871	17	302.8273	463.1979	2045.221	57872.45
3	139.897	102.843	41.871	17	301.6106	462.3907	2040.961	57755.19
4	139.646	102.835	41.715	17	301.1951	461.4481	2040.955	57754.93
5	139.688	102.877	41.479	17	301.0435	459.7676	2040.612	57756.96
6	139.986	102.735	41.475	17	301.1965	458.9425	2038.778	57705.01
7	139.761	102.706	41.478	17	300.9452	453.2964	2038.733	57703.61
8	139.671	102.701	41.475	17	300.8479	453.2844	2038.717	57702.56
9	139.579	102.701	41.475	17	300.7554	453.2952	2038.725	57703.26
10	139.576	102.701	41.475	17	300.7522	453.2952	2038.725	57703.26

Table 10 provides data on NOx, SO_2, and CO_2 emissions for a 300 MW solar power plant. This data is crucial for comparing the environmental impact of solar energy with that of a coal-fired power plant. For reference, Table 7 presents the emission data for a 300 MW coal-fired power plant.

Table 10 presents emissions data across ten iterations, revealing varying values for each. The minimum emissions were observed after the 8th iteration. This suggests that adjustments in the generating units, both thermal and solar, positively impact the reduction of NOx, SO_2, and CO_2 emissions.

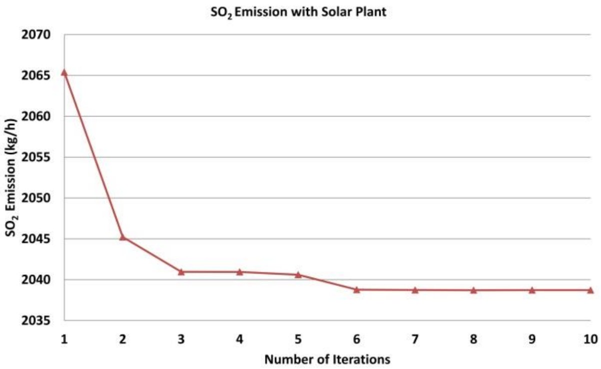

Fig. 5: SO_2 Emission with Solar Plant.

Fig. 5 illustrates SO_2 emissions with solar integration. This figure shows a reduction in NOx emissions compared to scenarios without a solar plant. In Fig presents NOX emissions with solar power, offering a visual representation of sulfur dioxide output from the plant, which is also lower compared to situations without solar energy. Finally, Fig. 6 displays CO_2 emissions with solar integration, emphasizing the reduced carbon dioxide levels associated with the plant's power generation compared to the absence of solar technology.

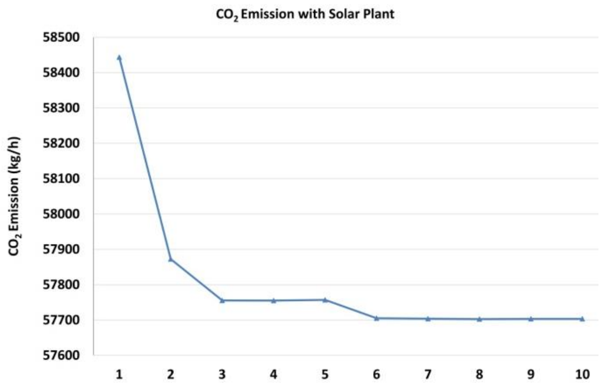

Fig. 6: CO_2 Emission with Solar Plant.

In comparing the 300 MW generation scenario with and without the solar power plant, we focus on how the emissions differ between the two setups. Specifically, Table 10 shows that the solar power plant has zero emissions for NOx, SO_2, and CO_2 due to its clean energy generation.

To assess the impact of integrating solar power, one optimal value from 10 iterations of performance and emission analysis will be used. This optimal value will provide insight into the best-case scenario for emissions reduction when coal-fired generation is replaced with solar power.

The integration of thermal and solar power plants for generating 300.8479 MW of electricity has yielded notable reductions in emissions. This section discusses the impact on key pollutants—NOx, SO_2, and CO_2—as presented in the respective tables.

Table 11: NOx Emission Comparison

Total Generation MW	NOx Emission (kg/h)		Reduction in %
	Only Thermal	Thermal+ Solar	
300.8479	481.6147	453.2844	5.88

Table 11 reveals a significant decrease in nitrogen oxide (NOx) emissions with the implementation of solar power. Specifically, the implementation of solar power reduced NOx emissions from 481.61 kg/hr to 453.28 kg/hr, signifying a 5.88% reduction. This reduction highlights the effectiveness of incorporating solar energy in lowering NOx emissions, which are critical for improving air quality and reducing smog formation.

Table 12: SO_2 Emission Comparison

Total Generation MW	SO_2 Emission (kg/h)		Reduction in %
	Only Thermal	Thermal+ Solar	
300.8479	2166.137	2038.117	5.92

Similarly, Table 12 demonstrates a marked reduction in sulfur dioxide (SO2) emissions. The data indicates a decrease from 2166.14 kg/hr to 2038.12 kg/hr, translating to a reduction of 5.92%. This reduction underscores the role of solar power in minimizing SO2 emissions, which are associated with acid rain and various environmental and health issues.

Table 13: CO_2 Emission Comparison

Total Generation MW	CO_2 Emission (kg/h) Only Thermal	Thermal + Solar	Reduction in %
300.8479	61308.79	57702.56	5.89

Table 13 presents the impact of solar power on carbon dioxide (CO_2) emissions. The implementation of solar energy led to a decrease in CO_2 emissions from 61,308.79 kg/hr to 57,702.56 kg/hr, reflecting a reduction of 5.89%. This significant drop in CO_2 emissions illustrates the potential of solar power to contribute to lower greenhouse gas emissions, thereby supporting efforts to mitigate climate change.
Overall, the adoption of solar power in thermal power generation has demonstrated a substantial environmental benefit by reducing emissions of NOx, SO_2, and CO_2. These findings highlight the effectiveness of integrating solar energy into conventional power generation systems, contributing to improved air quality and a reduction in greenhouse gas emissions.
These reductions underscore the environmental benefits of incorporating solar energy into power generation systems, demonstrating a clear improvement in air quality and a decrease in greenhouse gas emissions compared to traditional fossil fuel-based power plants.

4. Conclusions

In this paper, we addressed the problem of generating unit scheduling in thermal power stations for emission reduction, incorporating a solar energy system. The conclusions can be summarized as follows:

- Optimization of Scheduling: Since actual power requirements cannot be predicted in real-time, optimizing the schedule allows for emission reduction over the range of uncertainties.
- Effectiveness of Evolutionary Programming: The evolutionary programming method effectively reduces emissions of NOx, SO_2, and CO_2 in thermal power stations.
- Comparison with Solar Energy Integration: Results demonstrate that integrating a solar energy system yields better emission reductions compared to a standalone thermal power station (TPS) system.
- Impact on Emissions: A slight increase in the generation schedule results in a notable reduction in emissions, including NOx by 5.88%, SO_2 by 5.92%, and CO_2 by 5.89%.
- Cost Considerations: The same method can also be applied to determine the cost of generating unit scheduling.
- Overall Efficiency Improvement: The proposed approach enhances the overall efficiency of thermal power stations.

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