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Research Article

Equal Incremental Cost Method with Adjustable Gamma Control to Solve Generator Scheduling

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Abstract: Generator scheduling remains an intriguing issue within the energy industry. It involves the optimization of production costs, where system operators must select the optimal combination of available resources to minimize these costs. This research proposes an enhancement to the Equal Incremental Cost (EIC) Method using Adjustable Gamma Control (AGC) in generator scheduling. Iterations begin with an initial lambda value and gradually increase with the application of the γ factor until power demand is met. A γ variable of 10% is used as an adjustment step in the optimization method. The proposed method is capable of achieving convergence with 100% accuracy, where the power generated by all generators precisely matches the load demand (2,650 MW), at a cost of USD 32,289.03. EIC-AGC ranks second-best after VLIM, albeit with the consequence of consuming 195 seconds. This method is expected to have a significant impact on designing highly accurate generator scheduling techniques. Thus, generator scheduling will lead to a reduction in operational costs compared to current practices.

Keywords: Generator Scheduling, Equal Incremental Cost Method, Adjustable Gamma Control, Optimization

1 Introduction

Generator scheduling remains a critical concern in the energy sector, driven by various factors such as the persistent surge in energy demand, the evolution of novel generating technologies, and shifts toward cleaner and more sustainable energy practices. Efficient and reliable scheduling is imperative to meet this demand effectively. Advancements in generation technology and smart grid management present promising avenues for enhancing scheduling efficiency [1]. Additionally, government regulations and policies wield significant influence over the regulation and operation of power plants, thereby shaping scheduling strategies. Changes in energy policies can substantially impact the strategies employed in generator scheduling, reflecting the dynamic nature of the energy landscape [2,3].

Fuel costs typically constitute the primary expenditure in the operational budget of conventional power plants [4], particularly those reliant on fossil fuels such as coal, oil, and natural gas. These costs encompass various components, including fuel procurement, transportation, storage, and processing expenses. Beyond financial considerations, generator scheduling must also take into account critical technical factors such as generator ramp rate and start-up time [5]. Generator scheduling is indispensable in the operation of power plants, serving to minimize electricity production costs [6]. In practical terms, this scheduling method efficiently allocates the load to be borne by each available power plant, ensuring that electrical energy demand is met with minimal operating expenses [7]. This intricate process entails selecting the optimal combination of generating units and determining the generation level of each unit to meet the electrical energy demand at hourly intervals. By implementing generator scheduling, the system can significantly enhance resource utilization efficiency and streamline production costs, thereby ensuring profitability for both consumers and producers of electrical energy.

Continued efforts are underway to advance the development of more efficient, reliable, and sustainable scheduling techniques to meet the evolving demands of future energy requirements. A plethora of methodologies have been devised to address the challenges inherent in generator scheduling. For instance, Younes et al. leverage the Memory-Based Gravitational Search Algorithm (MBGSA) to optimize electricity generation via economic load dispatch, encompassing various sources such as photovoltaic (PV) systems, combined heat power (CHP) systems, and diesel generators [8]. Kumar et al. tackle the multiarea economic dispatch (MAED) problem utilizing Dynamic Particle Swarm Optimization (DPSO) and Gray Wolf Optimizer (GWO) to ensure compliance with generation constraints, transmission lines, and power balance across diverse system configurations, thereby minimizing fuel costs [9]. Additionally, Ozkaya et al. introduce the Adaptive Fitness-Distance Balance based Artificial Rabbits Optimization (AFDB-ARO) to address the complexities of the combined heat and power economic dispatch (CHPED) problem, characterized by its non-convex and discontinuous nature [10]. Alhasnawi et al. employ the Improved Butterfly Optimization Algorithm (IBOA) and Neighborhood Energy Management System (NEMS) to manage optimal consumption schedules for Home Energy Management Systems (HEMS), with the aim of flattening the aggregate curve of electricity consumption-generation and facilitating local direct electricity trading among numerous participants [11]. These studies collectively underscore the pivotal role of generator scheduling methods in enhancing the efficacy of generator scheduling, thereby reducing operational costs associated with electricity production. Furthermore, Raharjo et al. introduce the Large to Small Area Technique (LSAT), an artificial intelligence approach designed to ensure adherence to constraints in reaching the global minimum [12]. LSAT achieves this by scaling the feasible area until the best candidate solution point is identified, thus contributing to the optimization of generator scheduling processes.

The current Equal Incremental Cost (EIC) technique has limitations in terms of accuracy and efficiency in generator scheduling. Despite its widespread application, this method often fails to optimally adjust to changes in power demand, resulting in higher operational costs. One of the main issues is the lack of flexibility in real-time adjustment of Lambda values to meet dynamic power demands. Therefore, there is a need for the development of new techniques that can enhance the accuracy and efficiency of EIC in generator scheduling. This paper presents a pioneering method to elevate the EIC approach by integrating Adjustable Gamma Control (AGC) into generator scheduling, marking a key innovation [13]. The proposed methodology centers on iteratively identifying Lambda values that align with power demand criteria in incremental phases. The iterative process initiates with an initial lambda value and systematically augments it by incorporating a Gamma factor until the power demand is satisfied or nears adequacy. Anticipations suggest that this method will notably enhance the accuracy of economic dispatch techniques, consequently driving down operational costs in contrast to prevailing practices. The benefits of this development include improving efficiency in managing power generation resources, reducing fuel costs, and enhancing flexibility in responding to energy demand fluctuations. Overall, this innovation is expected to provide a more economical and sustainable solution for the power industry.

Organized into four distinct sections, this paper meticulously unfolds its discoveries. Initially, it furnishes a comprehensive overview of diverse methodologies employed in tackling generator scheduling challenges. Following this, the second section elucidates the proposed method in detail, bolstered by datasets for rigorous system testing. The third segment delves into the analysis of simulation results, facilitating subsequent discussions. Finally, the concluding section encapsulates the study's findings, delineates insightful conclusions drawn from the research, and charts potential pathways for future investigations.

2 Research Method

2.1 Generator Scheduling

Generator scheduling constitutes a pivotal optimization process within electric power system operations, aimed at ascertaining the most efficient power production from each available plant to satisfy current electrical energy demand while minimizing production costs [14]. The primary objective of generator scheduling is to mitigate the collective operational costs incurred by the active power plants [15]. In practice, this process entails solving complex optimization problems, encompassing various variables such as operational costs of generators, maximum and minimum capacity constraints of the plants, ramp rate limitations restricting the rate of change in electric power production within specific time intervals, and other technical constraints. The fundamental formula for generator scheduling is depicted in Equation 1 [16].

$$\min\left(\sum_{i=1}^{n} C_i(P_i) = a_i P_i^2 + b_i P_i + c_i\right) \tag{1}$$

Where, C_i is the total operational cost for generator i, P_i is the production of electrical power by generator i, and n is the total number of generators. The cost function $C_i(P_i)$

usually depends on the operational costs of generating i. This can be in linear or non-linear form, depending on the complexity of the model used.

In the realm of generator scheduling, the imposition of maximum and minimum generator capacity limits serves to uphold the integrity of electrical power production from each generator, ensuring it operates within a permissible range aligned with the physical capabilities of the generator [17]. Such constraints are indispensable for sustaining system stability and safeguarding the reliability of electrical energy supply. Typically, the maximum capacity limit ($P_{i,\max}$) is contingent upon the inherent physical constraints of the plant. These constraints pertaining to maximum and minimum capacity can be formally expressed through equation Equation 2.

$$P_{i,\min} \leq P_i \leq P_{i,\max} \tag{2}$$

This entails that the electrical power production (P_i) from generator i must not surpass its maximum capacity. Conversely, the minimum capacity constraint ($P_{i,\min}$) specifies the minimal threshold of electrical power production necessary to sustain stable plant operation. It is imperative that the electrical power production from generator i remains above the minimum capacity. Consequently, these dual constraints guarantee that the electrical power production of each generator operates within an acceptable range bounded by its minimum and maximum capacity.

2.2 Equal Incremental Cost Method with Adjustable Gamma Control (EIC-AGC)

The Equal Incremental Cost (EIC) method stands as a prominent technique within Economic Dispatch (ED), employed to ascertain the optimal distribution of electric power production across a range of available power plants [18]. This method is designed with the overarching goal of minimizing the total cost associated with electric power production, meticulously factoring in the technical constraints inherent to each generator. Within the framework of the Equal Incremental Cost Method, generators undergo a ranking process based on their margin costs, commonly known as equivalent incremental costs [19].

Implementing the EIC Method necessitates incremental steps toward achieving a convergent solution [20]. This algorithm operates by computing the Lagrange multiplier (λ) for each generator, representing the multiplier of each constraint, and employs a stepwise approach to adjust the electrical power production of each generator until convergence is achieved [21]. The EIC method is devised to ensure that the electricity generation plan minimizes fuel costs while fulfilling electricity demand. Through gradual refinement of the Lagrange multiplier value and electricity generation, as delineated in Equation 3, and the consequent reduction in Lagrange, depicted in Equation 4, the method effectively narrows the disparity between generation and demand while duly adhering to power generation constraints [22]. This systematic process culminates in the attainment of an efficient and precise economic solution.

$$\frac{dL}{dP_i} = \frac{\left(\sum_{i=1}^{n} C_i(P_i)\right) - \lambda\left(\sum_{i=1}^{n} P_i - P_D\right)}{dP_i} \tag{3}$$

$$P_i = \frac{(\lambda - b_i)}{2a_i} \tag{4}$$

The effectiveness of the incremental λ approach lies in its comprehensive consideration of diverse variables, encompassing fuel costs, generating capacity, and operational constraints [23]. This feature affords the power system operator a nuanced mechanism for allocating power generation, achieved through the gradual adjustment of the Lagrange multiplier and power generation value. Such a robust methodology enables the effective optimization of the generator scheduling problem, meticulously accommodating the limitations inherent to each power plant, and striking a harmonious balance between fuel consumption costs and the imperative of meeting electricity demand.

The EIC method is one approach used to find the λ value that meets the power demand criteria entered by the user. This method tries to find a value of λ that meets the power demand in a gradual manner. The iteration starts with an initial λ value, then the value is increased gradually until the power demand is met or approaches sufficiency. This section is part of an iteration in the process of finding a power production value that satisfies power demand.

$$\left|P_D - \sum_{\forall i} P_i\right| > 0.00001 \tag{5}$$

In Equation 5, this loop will continue to run as long as the difference between power demand (P_D) and total power produced ($\sum_{\forall i} P_i$) is greater than 0.00001. In this context, the value 0.00001 is the tolerance level for convergence, indicating that the iteration stops when the difference between the power demand and the total power produced is small enough.

$$\lambda(t+1) = \lambda(t) + \gamma \tag{6}$$

In Equation 6, λ here is a parameter in the formula for calculating power production (P). In each iteration, the λ value is added to the control value (γ). This is done to find a value of λ that meets the power demand criteria. In the first program, a variable γ is added to control the adjustment of λ in each iteration to find a solution that satisfies the given power demand. This is done by adjusting λ with certain increments in each iteration, which leads to a structured optimum value. In this case, the use of the variable γ introduces further regulation of how the Lagrange multiplier value is updated at each iteration. This makes it possible to regulate the convergence speed of the algorithm and the number of iterations required to produce a solution that satisfies the stopping criterion.

$$P_i = \frac{(\lambda + \gamma) - b_i}{2c_i} \tag{7}$$

Power production for each unit is calculated as in Equation 7. After the power production is calculated, it is checked whether the power production value for each unit is within the specified minimum and maximum limits. If it exceeds the maximum limit, power production will be set to the maximum allowed, and vice versa as in Equation 8.

$$P_i = \begin{cases} P_{i,\min}, & \text{if } \frac{(\lambda+\gamma)-b_i}{2c_i} < P_{i,\min} \\ P_{i,\max}, & \text{otherwise} \end{cases} \tag{8}$$

Initially, the first element of the array $\Delta P[0]$ is set equal to the power production of the first unit ($P[0]$). This step is necessary to start calculating the change in power production of the first unit. As long as the total power production ($\sum_{\forall i} P_i$) is greater than the input power demand (P_D), these steps are repeated.

$$\text{idx} = \text{argmax}(\Delta P_i) \tag{9}$$

$$\Delta P_{\text{idx}}(t+1) = \Delta P_{\text{idx}}(t) - 0.01 \tag{10}$$

$$\Delta P_{\text{idx}}(t+1) = \Delta P_{\text{idx}}(t) - \Delta P_{\text{idx}}(t-1) \tag{11}$$

The unit with the largest change in power production argmax(ΔP_i) is selected, and the power production of that unit is reduced by 0.01 as intended by Equation 9 and Equation 10. This is done to reduce total power production. After the power production is updated, recalculation is performed for the changes in power production of the related units $\Delta P_{\text{idx}}(t+1)$ as shown by Equation 11.

As long as the total power production $\sum_i P_i$ is less than the entered power demand P_D, these steps are repeated. The unit with the smallest change in power production argmax(ΔP_i) is selected, and the power production of that unit is increased by 0.01 as intended by Equation 12 and Equation 13. This is done to increase total power production. After the power production is updated, recalculation is performed for the changes in power production of the related units $\Delta P_{\text{idx}}(t)$ as shown by Equation 14.

$$\text{idx} = \text{argmin}(\Delta P_i) \tag{12}$$

$$\Delta P_{\text{idx}}(t+1) = \Delta P_{\text{idx}}(t) + 0.01 \tag{13}$$

$$\Delta P_{\text{idx}}(t) = P_{\text{idx}}(t) - P_{\text{idx}}(t-1) \tag{14}$$

This calculation process allows gradual adjustment of power production by adjusting the value of λ, thus enabling the search for a more efficient solution in achieving the desired power demand value. However, its effectiveness depends on choosing the right increment value and a suitable power production adjustment mechanism. This method is then used to rank power plants based on their equal incremental from lowest to highest. Once this sequence is determined, the allocation of electrical power production from each generator can be determined sequentially according to the electrical energy demand and technical limitations of each generator [24]. By using the Equal Incremental Cost Method with Adjustable Gamma Control, electric power system operators can produce optimal solutions to generator scheduling problems by considering cost efficiency and technical limitations of power plants. This method will be one of the superior approaches in industrial practice to optimize the allocation of electric power production in complex electric power systems.

2.3 Dataset for System Testing

Extensive testing was conducted to evaluate the suitability and efficacy of the Equal Incremental Cost Method with Adjustable Gamma Control approach. A pivotal facet of the evaluation process pertained to the meticulous selection of the dataset utilized in the testing phase. This dataset was deliberately chosen to facilitate a comprehensive exploration of the reliability and performance of the Equal Incremental Cost Method integrated with Adjustable Gamma Control across diverse scenarios and conditions. As evidenced by the data presented in Table 1 and Table 2, the testing employed a design featuring a 15-unit generator configuration sourced from IEEE, tailored to meet a substantial load requirement of 2,650 MW.

Table 1: Fuel cost coefficient

Unit	a (IDR/MW^2)	b (IDR/MW)	c (IDR)
1	0.000299	10.1	671.03
2	0.000183	10.22	574.54
3	0.001126	8.8	374.59
4	0.001126	8.8	461.37
5	0.000205	10.4	630.14
6	0.000301	10.1	1.661
7	0.000364	9.87	548.2
8	0.000338	11.5	227.09
9	0.000807	11.21	173.72
10	0.001203	10.72	175.95
11	0.003586	11.21	186.86
12	0.005513	9.9	230.27
13	0.000371	13.12	225.28
14	0.001929	12.12	309.03
15	0.004447	12.41	323.79

Table 2: Constraint (generation limits)

Unit	$P_{\min}$ (MW)	$P_{\max}$ (MW)
1	150	455
2	150	455
3	20	130
4	20	130
5	150	470
6	135	460
7	135	465
8	60	300
9	25	162
10	20	160
11	20	80
12	20	80
13	25	85
14	15	55
15	15	55

2.4 Pseudocode

The following is the pseudocode of the Equal Incremental Cost with Adjustable Gamma Control (EIC-AGC) method.

1. Initialization
   - P_i : Array (size 15) - output power (initial value zero)
   - ΔP_i : Array (size 15) - power changes (initial value zero)
   - λ : Value (0)
   - γ : Control value (adjustable, as example 0.1)
   - P_D : The desired total power
   - a, b, c : Fuel cost parameters
   - $P_{i,\min}, P_{i,\max}$: Array (unit capacity)
2. Iterations until demand is met
   - **Repeat** while ($|P_D - \sum_{\forall i} P_i| > 0.00001$) :
     - $\lambda(t+1) = \lambda(t) + \gamma$
     - $P =$ array of zeros (size(P_i))
     - For each unit (i)
     - **Calculate** P_i using the equal incremental cost method
     - **The limit** P_i within the capacity range
     - If $i > 0$, calculate ΔP_i.
3. Power Distribution Adjustment
   - **Repeat** while ($\sum_{\forall i} P_i > P_D$):
     - **Reduce** power from the unit with the highest $\Delta P_{\text{idx}}(t+1)$
     - **Update** P_i and $\Delta P_{\text{idx}}(t+1)$
   - **Repeat** while ($\sum_{\forall i} P_i < P_D$):
     - **Increase** power to the unit with the lowest $\Delta P_{\text{idx}}(t+1)$
     - **Update** P_i and $\Delta P_{\text{idx}}(t+1)$
4. Cost Calculation
   - Calculate $C_i(P_i)$ for each unit
   - Calculate $\sum_{\forall i} C_i(P_i)$ (The total unit cost amount)
5. Output
   - P_i : The optimal power distribution for each unit
   - $\sum_{\forall i} C_i(P_i)$: The minimum fuel cost achieved

3 Results

By disregarding channel losses and conducting a load test of 2,650 MW, the EIC Method with AGC adjusts its Gamma value by certain percentages, namely 10%, 50%, and 90%. These three Gamma values will be observed from three aspects, ranging from computational time to convergence, as well as the minimum cost solution produced and the total power generated.

Table 3 shows the demonstrates that the proposed method is capable of reaching convergence with 100% accuracy, where the generated power of all generators exactly matches

Table 3: Simulation results with the Gamma factor

Parameter	**Adjustable Gamma Control**		
	10%	**50%**	**90%**
Power(MW)	2,650	2,650	2,650
Cost ($\$/h$)	32,289.03	32,808.77	33,126.2
Time (s)	195	30.6	25.5

the load demand (2,650 MW), at a cost of USD 32,289.03. The variable γ is used as an adjustment step in the optimization method. When γ has a value of 10%, the steps of changing λ in seeking solutions are smaller compared to when γ has values of 50% or 90%. Thus, the convergence process towards the optimal solution will be smoother and tend to be more accurate because these smaller changes allow the algorithm to explore the solution space in more detail.

However, using γ with smaller values such as 10% leads to slower iterations in the solution search. This is because the smaller steps taken require more iterations for the algorithm to approach the optimal solution accurately. This results in longer computational time since the algorithm has to perform more calculations in the process of searching for the solution. On the other hand, when γ has larger values, such as 50% or 90%, the steps of changing λ become larger, which accelerates convergence towards the solution. However, with these larger steps, there is a possibility that the algorithm may "overshoot" the optimal solution or fail to approach the best solution accurately, especially if the system's distribution or stiffness requires finer adjustments.

So, although solutions obtained with larger γ values can be achieved with shorter computational time, they may not be as accurate as desired. On the other hand, with smaller γ values, solutions tend to be more accurate but require more time to reach. Therefore, the choice between using γ with values of 10%, 50%, or 90% will depend on the balance between the desired solution accuracy and the available computational time. Table 4 is illustrates the best combination when using Gamma 10%.

Table 4: Simulation results

Unit	**Power (MW)**	**Unit**	**Power (MW)**	**Unit**	**Power (MW)**
1	247.49	6	460	11	20
2	455	7	465	12	80
3	130	8	60.01	13	25
4	130	9	25	14	15
5	362,5	10	160	15	15

The method's reliance on a fixed Gamma for Lambda, where the parameter is increased by a constant value (e.g., Gamma = 10%, 50%, and 90%) in every iteration, poses potential limitations. This fixed incrementation strategy might not be suitable for all scenarios, particularly when the ideal adjustment for Lambda varies unpredictably. Consequently, the algorithm's ability to converge towards the optimal solution could be compromised, as it may overlook more nuanced changes in Lambda that could lead to better outcomes. This rigidity in Lambda adjustment could result in inefficiencies or inaccuracies, especially when facing complex optimization landscapes where the optimal Lambda change is not consistent across iterations. Thus, while the program offers a systematic approach, its reliance on a fixed increment for Lambda could hinder its efficacy in finding the most optimal power generation configuration.

4 Discussion

To validate the proposed method, it is compared against several other methods, the simulation results of which are presented in Table 5.

Table 5: Comparison of simulation results

Method	Power (MW)	Cost($\$/h$)	Time (s)
Dynamic Programming [25]	2650	32506	-
LSAT [25]	2650	32507	-
LIM [21]	2650	32549	2.6
ELIM [21]	2650	32542	0.12
VLIM [13]	2650	32183	0.004
ACC-PSO [26]	2659	32820	-
TVACPSO [27]	2650	32462	0.67
WIPSO [27]	2650	32464	0.78
CPSO [27]	2650	32467	0.69
PSO [27]	2650	32476	0.76
HNN [28]	2650	32568	-
MPSO [29]	2650	32465	1.87
GSCNHGWO [30]	2650	32687	14.9
ESCSDO [31]	2650	32692	2.9
PPSO [32]	2650	32543	3.47
Fuzzy-APSO [33]	2650	32548	8.7
EIC-AGC	**2650**	**32289.03**	**195**

EIC-AGC ranks second best after VLIM, but the trade-off is it consumes considerably more time than the others. The presented EIC-AGC utilizes an exact optimization approach. This exact approach directly computes the optimal solution based on the mathematical model of the given optimization problem. In this case, the program employs an iterative method that gradually adjusts parameters to approximate the optimal solution of the given problem.

The advantage of this approach lies in its ability to generate optimal solutions or at least solutions very close to optimality in certain cases. This approach ensures certainty that the generated solution is truly optimal according to the specified criteria. However, there are also some inherent limitations to this exact approach. One of them is the computational time required. Because the program systematically tries every possible solution or undergoes highly detailed iterative steps to approach the optimal solution, the time needed to complete the calculations can be very significant, especially for complex or large-scale problems. Although EIC-AGC can provide the best solution in terms of optimality, the sacrifice required is the time needed to reach that solution. In situations where time is not a crucial factor, such an exact approach can yield highly satisfying results. However, in situations where time is highly valuable and there is a high tolerance for non-optimal solutions, faster metaheuristic methods that may provide suboptimal solutions could be a better choice.

5 Conclusion

This research introduces a novel approach to optimizing generator scheduling, leveraging the Equal Incremental Cost Method with Adjustable Gamma Control. The simulation results show that the Gamma control can influence both the convergence in terms of time and the solutions produced. By setting Gamma closer to zero ($\gamma > 0$), there is a possibility of obtaining better solutions, but it may take more time. Conversely, if approaches one ($\gamma < 1$), there is a possibility that the solutions produced may not be as good, but the computational time could be shorter. However, it's also possible that setting ($\gamma < 1$) may result in significantly better solutions. Based on Table 5's comparison among methods, EIC-AGC emerges as one of the competitive methods, and even the best among the others. A drawback of EIC-AGC is its time-consuming nature. When used on a large scale, it will require a significant amount of time. Future endeavors will involve rigorous testing of the proposed method under dynamic loads, alongside comprehensive comparisons with various alternative methodologies.

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