

Contract-Oriented Optimal Economic Dispatch of Thermal Generators in a Multi-Area Deregulated Power System



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ABSTRACT: Bilateral contract between the Distribution Companies (DISCOs) and Generation Companies (GENCOs), modelled using DISCO Participation Matrix (DPM), has significant impact on the economic scheduling scheme of thermal generators in Multi-Area Power Systems (MAPS). Neglecting the contract while formulating the scheme can result in suboptimal solutions and inefficient utilization of resources. Thus, this paper proposed a DPM-constrained optimal Economic Dispatch (ED) scheme for multi-fuel type thermal generators in MAPS. The ED scheme minimized the fuel cost of the generators of each GENCO subject to the DPM, generation-demand balance, generation limits, and line transmission capacity as constraints. Due to its fast convergence, flexibility and global optimum searching mechanism, Cuckoo Search Algorithm (CSA) is used to solve the ED problem. The developed scheme is implemented on IEEE 39-bus and 52-bus Nigerian Power System (NPS) both partitioned into three CAs with multiple DISCOs and GENCOs. The effectiveness of the scheme is evaluated by simulating the systems in MATLAB environment. The performance of the ED on the IEEE 39-bus is evaluated by comparing it with those obtained using Grey Wolf Optimizer (MOGWO). It is observed that the fuel cost is reduced by 22.34%, from $5.655 \times 10^6 \$/h$ obtained using the MOGWO to $4.392 \times 10^6 \$/h$ with the developed CSA-based ED schemes. This signifies a substantial improvement over the MOGWO-based solution. Likewise, the ED scheme's performance on NPS is evaluated by comparing its performance with that obtained using Bat Algorithm (BA). For the 24-hour ED on the NPS, the fuel cost is reduced from $2.467 \times 10^6 \$/h$ to $1.953 \times 10^6 \$/h$, representing 20.85% reduction. These cost reductions emphasize the significance of imposing the DPM constraint as well as the superior optimization capability of the CSA algorithm in generating schedules that minimize fuel costs compared to the MOGWO and BA-based methods.

KEYWORDS: Cuckoo Search Algorithm, DISCO Participation Matrix, Distribution Companies, Economic Dispatch, Generation Companies, Nigerian Power System

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I. INTRODUCTION

Deregulation of power systems has gained significant momentum worldwide as countries seek to shift away from centrally controlled Vertically Integrated Utility (VIU) power systems. (Ahmed *et al.*, 2022; Athab & Majeed, 2020). This transformation is driven by several primary goals, including the introduction of competition, enhancement of efficiency, and provision of cost-effective electricity to consumers (Anil & Srikanth, 2018). In a deregulated power system, Generation Companies (GENCOs) and Distribution Companies (DISCOs) function as separate entities, operating independently within an open market framework (Sehrawat & Lather, 2019).

The key objective of power system deregulation is to foster competition among market participants, thereby encouraging innovation, cost reduction, and improved service quality (Azizivahed *et al.*, 2020). By dismantling the VIU monopoly structure, deregulation aims to create an environment where multiple GENCOs can generate electricity and compete to sell

it in the market (Basu, 2019). Likewise, DISCOs, also known as retail electricity providers, have the freedom to purchase electricity from various GENCOs, within or outside their Control Area (CA), and sell it to end consumers (Guo *et al.*, 2017; Kumar *et al.*, 2022).

Under a deregulated power system, the trading of electricity takes place in open markets. Market mechanisms, such as power exchanges and bilateral contracts, facilitate the buying and selling of electricity between GENCOs and DISCOs (Chen & Chen, 2021). These market mechanisms introduce flexibility and transparency, allowing market participants to negotiate prices and quantities of electricity based on supply and demand dynamics. Consequently, consumers benefit from a wider choice of electricity providers and competitive pricing (Sehrawat & Lather, 2019; Jian & Zhou-Jing, 2019).

Moreover, deregulation also aims to enhance the overall efficiency of the power system. By introducing competition,

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GENCOs are incentivized to optimize their generation strategies and minimize costs to remain competitive in the market (Chen *et al.*, 2023). This drive for efficiency can result in more economical generation practices, improved utilization of resources, and reduced operational expenses (Karri, 2013). Additionally, DISCOs are encouraged to enhance their distribution networks and customer service to attract and retain customers in a competitive market (Almansury & Al-Anbarri, 2023). Furthermore, deregulation seeks to provide cost-effective electricity to consumers. Increased competition in the market can lead to competitive pricing among GENCOs, offering consumers the opportunity to select electricity suppliers based on price, quality, and other value-added services. This competition-driven pricing can potentially lower electricity costs for end consumers, fostering affordability and accessibility (Musau *et al.*, 2016; Jadoun *et al.*, 2015)).

In addition, the GENCOs struggles to generate power at the minimum possible costs and transmission losses (Nguyen & Fujita, 2017). As such, optimal scheduling of thermal generators owned operated by the GENCOs is crucial for ensuring the efficient and reliable operation of deregulated Multi-area Power System (MAPS) (Guo *et al.*, 2017). This scheduling process involves determining the appropriate generation levels of thermal units at different time intervals to meet the forecasted load demand while taking into account various operational constraints. By implementing effective scheduling, it is possible to minimize generation costs, maintain a balance between supply and demand, and optimize the utilization of available resources. Various research efforts have addressed ED in MAPS (Kunya *et al.*, 2023). For

instance, Sakthivel & Sathya, (2021) proposed the use of a Fuzzified Squirrel Search Algorithm to solve the Single-Area Multi-Fuel ED (SAMFED) and Multi-Area Multi-Fuel ED (MAMFED) problems. The SAMFED aims to find the optimal generation schedule for a single area, while MAMFED focuses on optimizing power transfers between different areas while considering fuel alternatives and various constraints. In Yu *et al.*, (2023), a novel hierarchical reinforcement learning architecture for solving the multi-area economic dispatch (MAED) problem in a fully off-line optimization manner is presented. The proposed architecture transforms the MAED problem into an augmented sub-MAED problem and utilizes distributed Q-learning and multi-stage decision algorithms to calculate the optimal output power within each area. While in (Sehrawat & Lather, 2019), an intelligent, agent-based approach for ED in a MAPS is proposed by utilizing a multi-agent system with a consensus method, eliminating the need for a central controller and reducing computational efforts.

In a similar study (Yin & Sun, 2022), presented the challenges faced by traditional centralized ED optimization methods such as slow calculation speed, privacy concerns, and limited consideration of multiple cost objectives is addressed. Multi-objective grey wolf optimizer (MOGWO) optimizes the sub-problems of each area independently while sharing only limited boundary bus information between areas, enabling overall optimization (Sakthivel & Sathya, 2021; Shao *et al.*, 2023). A distributed models are presented in Yin & Cai, (2024a) and Yin & Cai, (2024b) with hierarchical structure that significantly reduced the computational complexities. Other similar studies reviewed are summarized in Table 1.

Table 1 Research works on multi-area economic dispatch

Ref	Structure	System size		Optimization		Remarks
		No. of units	No. of CAs	Objective function	Optimizer	
(Sharifian & Abdi, 2025)	Distributed	40 units	4	Single	CrSA	Both deterministic and stochastic models were presented, though the impact of the uncertainties on the fuel cost was not evaluated. As a model-based controller, MPC requires full knowledge of the system states. However, the mechanism by which the states are provided to the controller is unclear.
(Zhou <i>et al.</i> , 2024)	Distributed	Not specified	1	multiple	MPC	
(Yin & Cai, 2024(a))	Distributed	10 units & 54 units	3	multiple	MMOHDCM	Each CA computes its outputs independently. This disjointed computation is at the detriment of the computational complexity. As a heuristic intelligent technique, the method relied on stochastic processes, which can lead to inconsistent results across different runs and generally do not guarantee global optimality.
(Yin & Cai, 2024(b))	Distributed	482 units	2, 8	multiple	HDMOMIA	
(Spea, 2024)	Centralized	5, 6, 24, 40 units	1	multiple	MRFO	The MRFO's potential scalability issues and computational overhead when applied to very large-scale power system dispatch problems is not established.
(Wang, et al., 2024)	Centralized	40, 120, 140 units	2, 4	single	CLDE	Altering the mutation and crossover mechanisms in the CLS can disrupt structured learning, imbalance exploration and exploitation.
(Nordström, et al., 2024)	Centralized	Nordic system	11	multiple	Analytical-PIM	The accuracy of the PIM remains uncertain, as interpolating hourly data to minute-by-minute variations can introduce errors, hence the need to validate using higher-resolution historical data.
(Hoballah & Azmy, 2023)	Centralized	66-bus, 16 units	3	multiple	HGWMPA	Although the aim is to minimize the fuel cost and reducing transmission line congestion, the objective function (OF) does not explicitly account for the congestion aspect.
(Lai <i>et al.</i> , 2022)	Centralized	5,7,10, 140 units	1	multiple	MSA	Without proper parameter setting, the MSA can suffer from poor convergence, uneven prioritization of objectives, and unreliable trade-offs due to inadequate guidance while exploring the solution space.
(Chen & Tang, 2022)	Centralized	10, 40, 120 units	2, 3, 4	single	ImCSO	Improving the CSO by adjusting its learning and updating mechanisms can result in increased computational complexity and parameter sensitivity.

(Yin & Sun, 2022)	Distributed	10 units & 54 units	3	multiple	GWO	Optimizing the CA generations independently while sharing only partial information from nearby CAs can lead to suboptimal coordination, causing inconsistencies in power dispatch.
(Cheng et al., 2021)	Centralized	33 bus DN	1	Multiple	HTL-MOPSO	Validation on the IEEE 33-bus system is inadequate, as it is a radial distribution network, whereas ED studies are more appropriately validated on transmission networks like the IEEE 14- or 30-bus systems.
(Zare et al., 2021)	Centralized	10 and 40 units	3, 4	single	IFA	Improper selection of penalty factors for constraints handling is generally challenging, hence the study proposed a new penalty-free approach for the ED.
(Li, 2021)	Centralized	30 bus, 5 units	1	multiple	IPSO	Using multiple fitness values for each particle can complicate the optimization process by making it harder to balance the conflicting ED objectives.
(Shao et al., 2021)	Distributed	5 and 10 units	1	multiple	MOPPO	The reliance on the slack variables and penalty relaxation can introduce approximation errors and compromise dispatch accuracy, especially under dynamic load conditions.
(Sakthivel et al., 2021)	Centralized	6, 10, 40 units	1	Single and multiple	SSA	Due to the conflicting objectives of fuel cost and emissions, a weighted sum price penalty factor is used to unify the bi-OF, while a fuzzy decision strategy selects the best compromise from the Pareto optimal front.
(Sakthivel & Sathya, 2021)	Centralized	10 units	3	single	FSSA	The reliance on the weighted sum method can limit the exploration of the entire Pareto front, especially in non-convex regions, potentially leading to skipping some optimal trade-offs between fuel cost and emissions.
(Azizivahed et al., 2020)	Distributed	40 units	1	Multiple	WOA	WOA has the tendency to prematurely converge to local optima, especially when VPLE is considered making the ED highly dimensional and non-linear.
(Schrawat & Lather, 2019)	Distributed	14-bus, 11 units	4	Single	DA	Using approximated OF can impair on the accuracy of the ED model.
(Yazdandoost et al., 2018)	Distributed	6 and 40 units	2, 4	Single	ESOA	Minimizing cost by transmitting power from lower-cost CA to higher-cost areas can reduce the total cost, however it can lead to violations of tie-line capacity constraints.

Despite the various contributions of these studies, most of the existing scheduling schemes in MAPS overlook the significance of the bilateral contracts between DISCOs and GENCOs and their impact on the schemes. These contracts defined by the DISCO Participation Matrix (DPM) outline the participation factors of each GENCO in each Control Area (CA) and their contractual obligations with each DISCO within or outside the CA. Failure to consider the DPM in the MAED can lead to suboptimal solutions and inefficient resource allocation.

To address this gap, this study developed a DPM-constrained optimal scheduling scheme specifically designed for thermal generators in MAPS. The scheduling scheme takes into account the DPM, capturing the participation factors of each GENCO in each CA and their contractual obligations with DISCOs. By incorporating the DPM into the scheduling process, the scheme seeks to enhance the effectiveness of the optimization process while ensuring compliance with contractual obligations and other constraints. Specifically, the contributions of this study are itemized as

- Incorporating the DISCOs – GENCOs bilateral contractual obligations (modelled using DPM) in the formulation of MAMFED problem,
- Application CSA for the solution of MAMFED with distributed architecture,
- Demonstrating the effectiveness of the scheme on both analytical (IEEE 39-bus) and real-life (52-bus Nigerian Power System) systems both partitioned into three CAs.

After this introductory section, Section II discusses ED scheme in deregulated power system. The formulation of the proposed distributed MAMFED is presented in Section III,

while section IV discusses the simulation results. The paper is concluded in Section V.

II. ECONOMIC DISPATCH IN A DEREGULATED SYSTEM

Conventionally, ED involves allocating the power generation among various units in a manner that minimizes the overall production costs while satisfying system reliability and operational constraints. While in MAPS, ED is used to coordinate generation schedules and inter-CA energy transactions among nearby CAs while minimizing the overall fuel cost devoid of violating any the constraint. ED can be implemented in either centralized or distributed manner.

A. Centralized and distributed Economic Dispatch model

In the centralized approach, the central dispatch center receives the online information about the generation level of each unit centrally, P_{Gi}^t as shown in Figure 1. Using the information, the dispatch command signals, μ_{G4}^{t+1} are generated at the dispatch center and transmitted to each unit for the next

schedules.

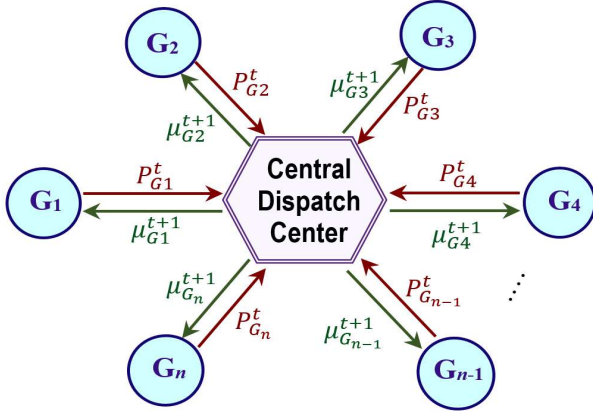


Figure 1 Centralized ED architecture

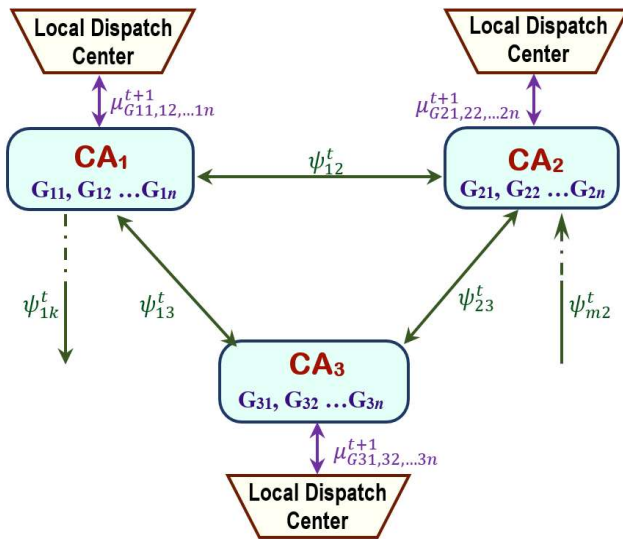


Figure 2 Distributed ED model

However, with the recent exponential growth of PS, the traditional centralized ED programmes suffers numerous setbacks like slow computational speed, communication congestion leading to excessive communication delay, and vulnerability to security attacks. Hence distributed approach is preferred (Yin & Sun, 2022).

In distributed approach, each CA has its local dispatch center and shares the information about the generation level of each unit and other ancillary services with its adjacent CAs, as depicted in Figure 2.

B. DISCOs Participation Matrix (DPM)

The DISCOs-GENCOs bilateral contracts are defined using the DISCOs participation matrix (DPM). The number of DPM rows indicates the number of GENCOs (\mathcal{J}), while the number of columns denotes the number of DISCOs (ψ) in the network. DPM diagonal elements represent the contractual agreement between GENCOs and DISCOs situated within the same CA. While the off-diagonal elements represent the power contract across different CA as shown in (1).

$$DPM = \begin{pmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1\mathcal{J}} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2\mathcal{J}} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{\psi 1} & \lambda_{\psi 2} & \cdots & \lambda_{\psi \mathcal{J}} \end{pmatrix} \quad (1)$$

The elements of DPM known as contract participation factor (cpf), λ_{ij} is a fraction of i th DISCO's LM requirement contracted to the j th GENCO. It can be deduced that:-

- The block diagonals, λ_{ij} ; $\forall i = j$ correspond to CA local demands.
- Off diagonal blocks λ_{ij} ; $\forall i \neq j$ indicate the demands of the DISCOs in one area to the GENCOs in another area.
- The sum of all element in a column/row in the DPM is unity, as expressed in (2)

$$\sum_{i=1}^{\psi} \lambda_{ij} = 1; \quad \forall j \quad (2)$$

- If $\lambda_{ij} = 0$, there is no LM contract between DISCO i and GENCO j , thus, $0 \leq \lambda_{ij} \leq 1$,

Therefore, the power generation of each GENCO in i th CA based on its contract with the DISCOs can computed based on the DPM as shown in (3) (Lekshmi & Balamuruga, 2017)

$$\begin{pmatrix} P_{G_{i,1}} \\ P_{G_{i,2}} \\ \vdots \\ P_{G_{i,\mathcal{J}}} \end{pmatrix} = \begin{pmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1\mathcal{J}} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2\mathcal{J}} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{\psi 1} & \lambda_{\psi 2} & \cdots & \lambda_{\psi \mathcal{J}} \end{pmatrix} \begin{pmatrix} P_{D_{i,1}} \\ P_{D_{i,2}} \\ \vdots \\ P_{D_{i,\psi}} \end{pmatrix} \quad (3)$$

III. MAMFED FORMULATION

The objective of the MAMFED is to minimize the total fuel cost of generators, owned and operated by GENCOs in all CAs through the coordinating the generation levels and cross-border energy.

A. Objective function

The objective function of the MAMFED is formulated as $\min(F)$, where F is the total cost of fuel of the thermal units in all the CAs, defined as

$$F = \sum_{i=1}^N \sum_{j=1}^{\mathcal{J}} F_{ij}(P_{G_{ij}}) \quad \forall t(\text{hour}) \quad (4)$$

Where N is the number of CAs in the MAPS (3, in this regard), \mathcal{J} is the number of GENCOs, while F_{ij} and $P_{G_{ij}}$ are the fuel cost and power generation by j th GENCO in i th CA.

In this paper, a quadratic-trigonometric polynomial functions of generated power shown in (5) is used.

$$F_i = a_i + b_i P_{G_i} + c_i P_{G_i}^2 + |e_i \cdot \sin f_i (P_{G_i}^{\min} - P_{G_i})| \quad (5)$$

Where a_i , b_i , and c_i are the cost coefficient of generators.

B. Constraints

The constraints considered are the GENCO-DISCO bilateral contract defined by the DPM (as formulated in (1) –

(3)), generation-demand balance, and tie-line transmission capacity.

A. Generation-demand balance in MAPS

The generation-demand balance constraint is formulated such that power generation from all the GENCOs, the total demand, and the transmission losses, P_{loss} are equal as shown in (6),

$$\sum_{i=1}^3 \sum_{j=1}^{\mathcal{J}} P_{G_{ij}} + \sum_{i=1}^3 \sum_{j=1}^{\psi} P_{D_{ij}} - \sum_{l=1}^3 P_l^{loss} + \sum_{i=1}^3 P_i^{tie} = 0 \quad (6)$$

Where P_l^{loss} is the transmission loss along the l th tie-line in the system expressed in (7),

$$P_L = \sum_{i=1}^3 \sum_{j=1}^3 P_{G_i} \beta_{ij} P_{G_j} + \sum_{i=1}^3 \beta_{oi} P_{G_i} + \beta_{oo} \quad (7)$$

The P_i^{tie} defining the aggregate power exchange between DISCOs and GENCOs operating in different CAs, as in (8)

$$P_i^{tie} = \sum_{i=1}^{10} \sum_{j=1, i \neq j}^{10} \lambda_{ij} P_{G_i} + \sum_{k=1}^{10} \sum_{i=1}^{10} \lambda_{ik} P_{D_k} \quad (8)$$

Where contract participation factor, λ defines the fraction of DISCO's LM requirement contracted to the GENCOs in different CAs. The first term of (8) models the contractual agreement between DISCOs in i th CA with GENCOs in j th CA, while the second represent the contract between DISCOs in different CA to the GENCOs in the same i th CA.

B. Generation limits

The output power of each generator is constrained within certain pre-defined lower and upper limits as expressed in (9)

$$P_{G_k}^{min} \leq P_{G_k} \leq P_{G_k}^{max}; \quad k = 1, 2, \dots, 10 \quad (9)$$

C. Tie-lines transmission capacity

The transmission lines interconnecting the multiple CAs need to be constrained within certain upper limit that should not exceeded due to contract violation and technical considerations. This constraint is expressed in (10):

$$P_{ij}^{tie} \leq P_{G_{ij}}^{tie-max} \quad (10)$$

IV. APPLICATION OF THE CUCKOO SEARCH ALGORITHM

To solve the proposed MAMFED problem, Cuckoo Search Algorithm (CSA) is applied.

A. Concept of CSA

CSA is a powerful meta-heuristic optimization technique inspired by the unique reproductive strategy of cuckoo birds, which lay their eggs in the nests of other birds. Developed by (Yang & Deb, 2009) CSA utilizes a combination of Lévy flight-based random walks and an elitist selection mechanism

to efficiently explore and exploit the solution space. This approach enables CSA to effectively navigate complex optimization landscapes, making it particularly useful for solving nonlinear and constrained optimization problems like the ED.

The algorithm is particularly well-suited for solving the MAMFED problem. The algorithm's ability to avoid local optima ensures high-quality solutions even in the presence of complex constraints such as valve-point effects, prohibited operating zones, and transmission losses. Additionally, CSA exhibits fast convergence due to its efficient exploration strategy, making it computationally effective for large-scale MAPs. Its flexibility and robustness allow it to handle real-world uncertainties, ensuring a reliable and cost-effective power generation schedule while maintaining system stability and efficiency.

B. CSA Implementation for the MAMFED

The CSA is implemented to solve the MAMFED formulated in (4) and (5) subject to the constraints modelled in (6) – (10). Table 2 presents the pseudo code that summarizes the implementation steps.

Table 2 Pseudo Code for the implementation of the CSA

Initialize the CSA parameters and generators' parameters:
 CSA parameters: step size, σ_u , lévy flight exponent, β , scaling factor, μ , step angle, ϑ ,
 Generators' parameters: a_i , b_i , c_i , β_{ij} , β_{oi} , β_{oo} , $P_{G_i}^{min}$, $P_{G_i}^{max}$, $P_{G_{ij}}^{tie-max}$, ψ , \mathcal{J} , λ_{ij}
Generate initial population of nests with eggs ($P_{G_k}^{init}$) for each GENCO in each CA, such that:
 $P_{G_k}^{min} \leq P_{G_k}^{init} \leq P_{G_k}^{max}$, $\forall k$
Evaluate fitness of each nest:
 Compute total fuel cost F using (4)
Check constraints:
 Generation-demand balance (6)
 Tie-line power exchange (8)
 Generation limits (9)
 Transmission capacity (10)
Apply penalty function for constraint violations
While stopping criteria not met (iteration $< \text{iter}_{max}$):
Generate new solutions using Lévy flight:
 $P_{G_k}^{new} = P_{G_k}^{init} + \alpha * \text{Lévy}(\beta)$
 Ensure new solutions remain within generation limits (9)
Evaluate fitness of new solutions;
Apply elitist selection: Replace worst nests with best solutions based on survival rate
 Update the best solution found so far, $P_{G_k}^{opt}$;
 Return the best solution:
 - Assign optimal power generation schedule for GENCOs; $P_{G_k}^{opt}: k = 1, 2, \dots, \mathcal{J}$
 - Total minimized fuel cost, F
End

Figure 3 shows flowchart of the developed CSA-based ED.

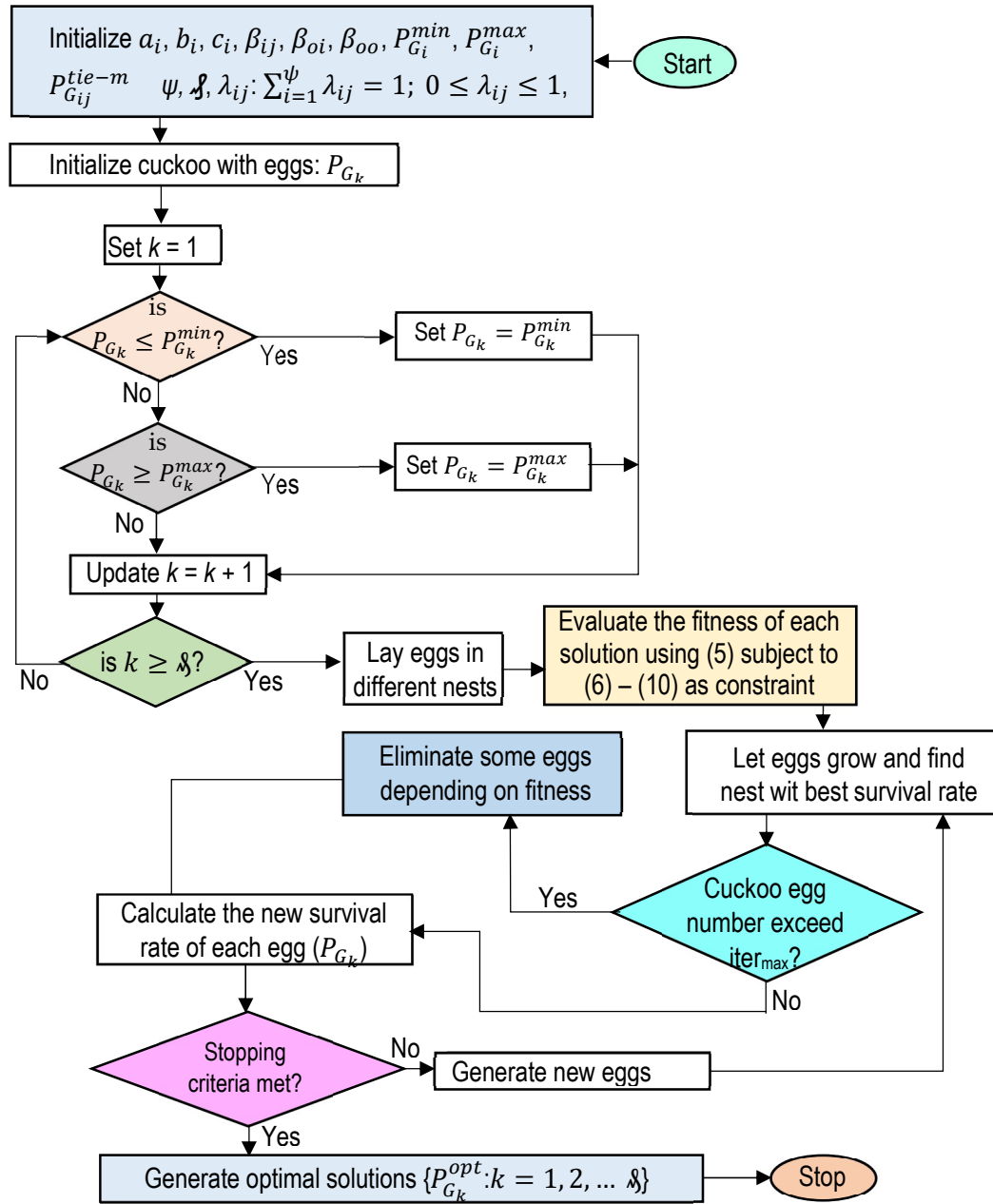


Figure 3 Flowchart of the developed CSA-based ED scheme in MAP

V. RESULTS AND DISCUSSION

To assess the effectiveness of the proposed scheduling scheme, the two systems considered are modelled and simulated in MATLAB. It is implemented on IEEE 39-bus and Nigerian Power System (NPS), both partitioned into three CAs with multiple DISCOs and GENCOs.

D. ED Scheme on IEEE 39-Bus System

Figure 4 depicts the partitioned IEEE 39-bus, while Table 3 summarized the composition of the CAs and the location of the GENCOs.

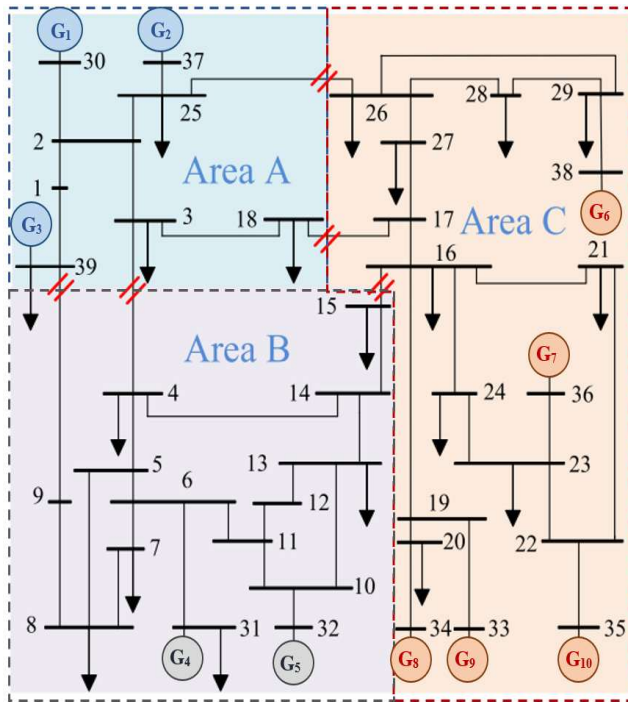


Figure 4 Partitioned IEEE 39-bus System

Table 3 GENCOS Locations in IEEE 39-bus

CAs	GENCOS: Location
A	G ₁ : bus 30, G ₂ : bus 37, G ₃ : bus 39.
B	G ₄ : bus 31, G ₅ : bus 32.
C	G ₆ : bus 33, G ₇ : bus 34, G ₈ : bus 35, G ₉ : bus 36, G ₁₀ : bus 38

In this study, the IEEE 39-bus system is loaded with load profile shown in Figure 5. The developed ED scheme is then applied to minimize the fuel cost of the 10 GENCOS subject to the constraints.

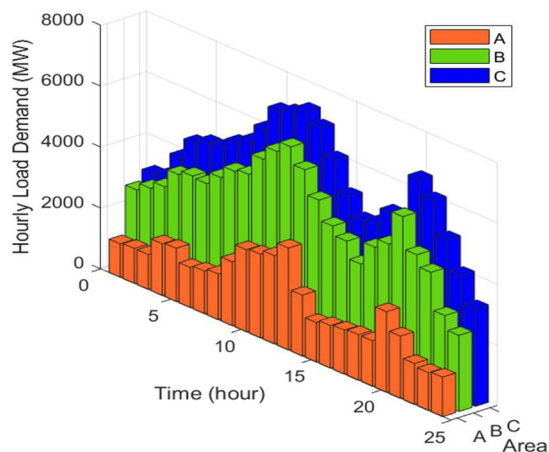


Figure 5 Daily Load demand for IEEE 39-bus system

The load demand profile has the daily averages of 1775.8MW, 4290.4MW and 5227.5MW for the areas A, B and C respectively, as shown in Table 4. Subsequently, various schemes were used for comparative analysis using the daily fuel cost as the performance metrics.

Table 4 Daily Load demand for IEEE 39-bus system

Time (Hour)	Load demand (MW)		
	Area – A	Area – B	Area – C
1:00	1100	2700	3050
2:00	1150	2950	3170
3:00	1150	3200	3970
4:00	1700	3800	4650
5:00	1750	3950	4850
6:00	1320	3900	4900
7:00	1400	4300	5250
8:00	1500	4700	5500
9:00	2100	4800	6100
10:00	2700	5500	6900
11:00	2750	5950	7050
12:00	2900	6300	7300
13:00	3350	5750	6950
14:00	2000	4950	6100
15:00	1300	4300	5100
16:00	1400	4000	4500
17:00	1450	3450	4600
18:00	1500	4200	5150
19:00	1500	4500	5200
20:00	2650	5600	6650
21:00	2050	4550	6150
22:00	1350	4170	5070
23:00	1250	2950	4100
24:00	1300	2500	3200
Average	1775.8	4290.4	5227.5

The Area Participation Factors (APF) are defined to model the contractual agreement between the control areas. In this study, the APFs are chosen arbitrarily as 0.25, 0.30 and 0.45 for area A, B, and C, respectively. They are chosen arbitrarily since they are determined by market forces in real scenario. With these APFs, the GENCOS from the three control areas are expected to meet up with their contract obligations by generating 25%, 30% and 45% of the total demanded power in the entire system respectively. For instance, at 09:00am, the optimal generations are 3250MW, 3900MW and 5850MW from area A, B and C respectively.

From the results, it is found out that the developed CSA-based ED determined the optimal generations by assigning optimal contract participation factor, λ to each GENCOS, as summarized in Table 5. As a hard constraint, all the λ 's in each area added up to the area's APF.

Figure 6 shows the optimal generation from the GENCOS in area A. It shows how the 25% of the total generation allocated to area A is optimally shared to GENCOS by the developed ED

Table 5: Optimized λ for IEEE 39-bus System

Area	APF	GENCOS	λ
A	0.25	G ₁	0.07
		G ₂	0.095
		G ₃	0.085
B	0.30	G ₄	0.138
		G ₅	0.162
		G ₆	0.0675
C	0.45	G ₇	0.1035
		G ₈	0.081
		G ₉	0.090
		G ₁₀	0.108

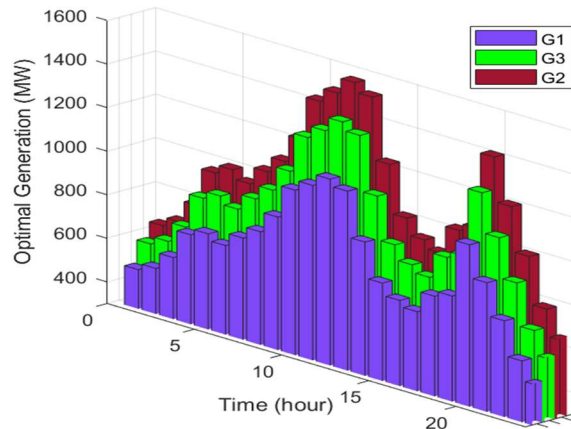


Figure 6 Optimal Participation of area A GENCOs

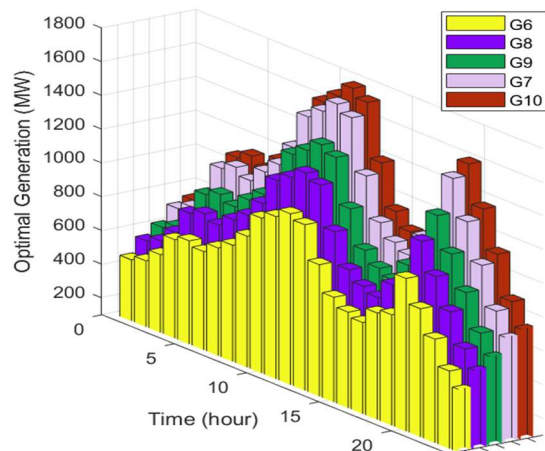


Figure 7 Optimal Participation of area C GENCOs

As summarized in Table 5, the three GENCOs, G₁, G₂ and G₃ in area A optimally generate power in the ratio of 0.07:0.095:0.085 to meet up with the 25% generation share.

For instance, at 16:00, the generations from area A are 693.00MW, 940.5MW and 841.5MW from G₁, G₂ and G₃ respectively, which corresponds to the optimal λ shown in Table 5. Figure 7 and 8 show the optimal participations of GENCOs in areas B and C respectively.

In the same way, the optimal λ of the area C are 0.0675, 0.1035, 0.081, 0.09 and 0.108 for G₆, G₇, G₈, G₉, and G₁₀ respectively, which optimally add to the 45% of the generation share. For instance, at 23:00 hour, 3735MW (representing 45% of the total hourly demand of 8300MW) is obliged to area C

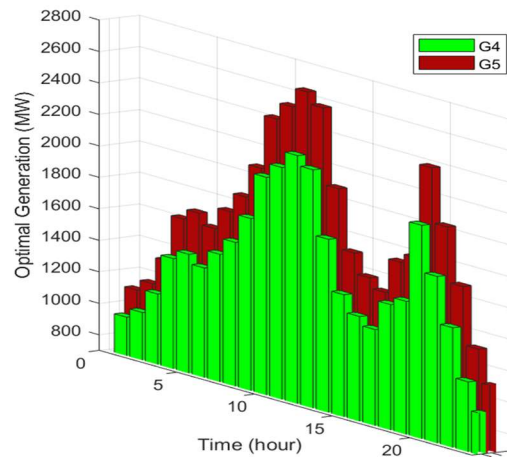


Figure 8 Optimal Participation of area B GENCOs

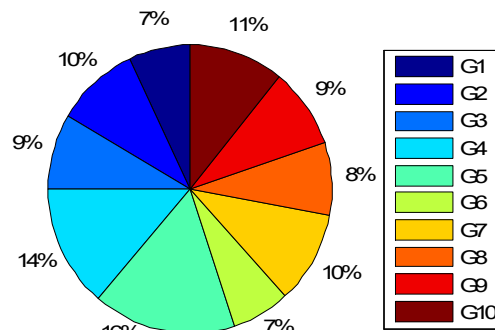


Figure 9 Optimal generation share for IEEE 39-bus system

The developed ED optimally allocated the generation levels as 560.25MW, 859.05, 672.3MW, 747.00 and 896.40 to G₆, G₇, G₈, G₉, and G₁₀ in order to meet up with 3735MW at reduced fuel cost, devoid of violating the rest of the constraints. The overall generation share from all the 10 GENCOs is as shown in Figure 9.

To ascertain the effectiveness of the scheme, the total generation cost is compared other optimal schemes. From the simulations, it is observed that the fuel costs GENCOs in area A, B and C are found to be 1.216×10^6 , 1.326×10^6 and 1.142×10^6 \$/hr, adding up to 3.684×10^6 \$/hr, as summarized in Table 6.

Table 6 Comparative Analysis on the Fuel Cost

Schemes	Fuel cost (\$/hr) $\times 10^5$			
	Area A	Area B	Area C	TOTAL
MMOHDCM	1.741	1.900	1.636	5.277
CLDE	2.048	2.235	1.924	6.207
HGWMPA	1.678	1.831	1.576	5.085
ImCSO	1.799	1.963	1.69	5.452
IFA	1.505	1.642	1.413	4.560
FSSA	2.08	2.522	1.702	6.304
WOA	1.449	1.581	1.362	4.392
GWO	1.406	1.534	1.322	4.262
DA	1.81	1.979	1.866	5.655
Proposed	1.216	1.326	1.142	3.684

Comparatively, the developed scheme not only provides superior cost reductions but also demonstrates faster

convergence than the other algorithms, as shown by the convergence curves for 100 iterations in Figure 10.

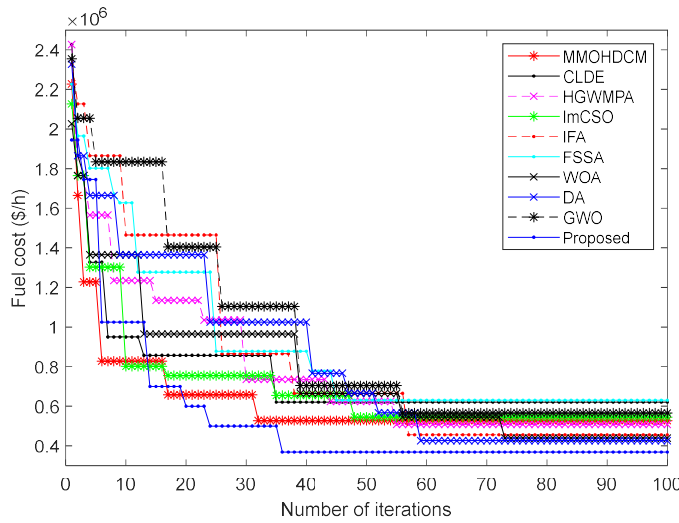


Figure 10 Convergence curves for IEEE 39-bus System

The superior performance of the CSA is as a result of the careful selection of the number of iterations and the parameters s , ϑ , μ and β as summarized in Table 7.

Table 7 CSA Parameters

Parameter	Ranges	Value chosen
Step size parameter, σ_u	0.1 – 1	0.45
Lévy Flight Exponent, β	1 – 2	1.5
Scaling Factor, μ	1 – 1.5	1.2
Step angle, ϑ	0.1 – 1	0.78
Number of iterations	---	100

E. Developed ED Scheme on NPS

To establish its effectiveness on real-life system, the developed CSA-based ED is implemented on 52-bus Nigerian Power System (NPS) partitioned into three CAs with 8 GENCOS. Area A of the system has two GENCOS (G_1 and G_2), while B and C have three GENCOS each, (G_3 , G_4 and G_5) and (G_6 , G_7 and G_8) respectively, based on the data obtained from [42].

Table 8 Daily Load demand for NPS

Time (Hour)	Load demand (MW)		
	Area – A	Area – B	Area – C
1:00	380	1280	1840
2:00	650	1680	2060
3:00	700	1800	2080
4:00	860	1840	2260
5:00	820	1820	2460
6:00	540	1668	2028
7:00	1500	1180	1640
8:00	1720	1800	1280
9:00	2580	1380	1840
10:00	2780	1680	2060
11:00	2120	1800	2080
12:00	2460	1840	1960
13:00	2320	2220	2160
14:00	2540	1668	2028
15:00	1960	1580	1640

16:00	1820	1500	1280
17:00	880	1680	1840
18:00	600	1680	1860
19:00	860	1800	2080
20:00	1260	2040	2460
21:00	820	1820	2460
22:00	840	1668	2028
23:00	600	1180	1640
24:00	720	1000	1280
Average	1347.1	1650.2	1931.0

The system is loaded with 24-hour load profile shown in Figure 11. The load demand profile has daily averages of 1347.1MW, 1650.2 and 1931.0MW for the areas A, B and C respectively, as shown in Table 8

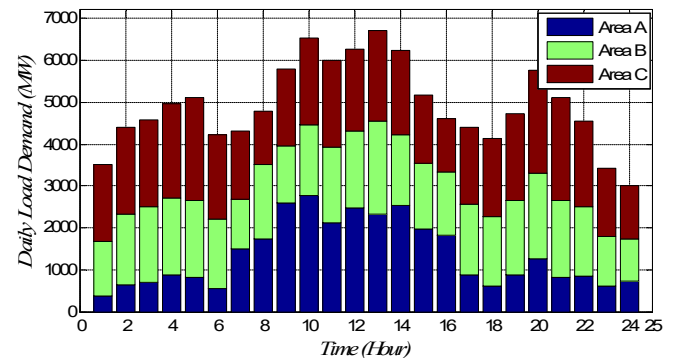


Figure 11 Daily Load demand for NPS

As in the previous scenario, the APF were assigned to define the contractual obligations between the areas, with values of 0.20, 0.45, and 0.35 for Areas A, B, and C, respectively. These factors dictate the ratio of generation across the areas, which is maintained at 0.2:0.45:0.35 (4:9:7). For example, at 01:00 AM, the generation capacities are distributed as 700 MW, 1575 MW, and 1225 MW for Areas A, B, and C, respectively.

Table 9 Optimized Contract Participation Factor for NPS

Area	APF	GENCOS	λ
A	0.20	G_1	0.084
		G_2	0.1160
B	0.45	G_3	0.1125
		G_4	0.2025
		G_5	0.1350
C	0.35	G_6	0.0945
		G_7	0.133
		G_8	0.1225

From the results, it is observed that the developed CSA-based ED determined the optimal generations by assigning optimal λ to each GENCOS.

Figure 12 shows the optimal generation from the GENCOS in area A. It shows how the 20% of the total generation allocated to area A is optimally shared by the developed ED among the GENCOS. As summarized in Table 9, the two GENCOS, G_1 and G_2 in area A optimally generated power in the ratio of 0.084:0.1160 to meet up with the 20% generation

share. This similar to area B with the optimal participations shown in Figure 13.

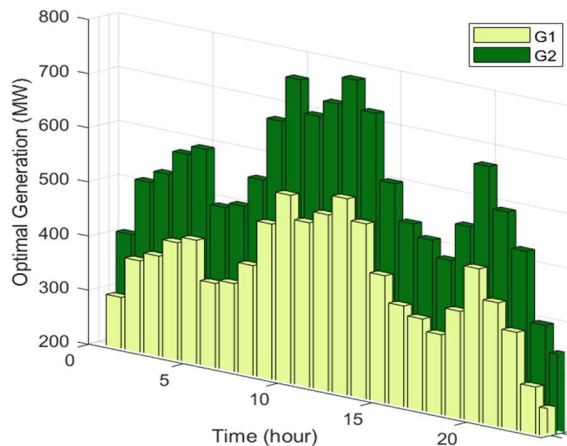


Figure 12 Optimal Participation of GENOS in area A of NPS

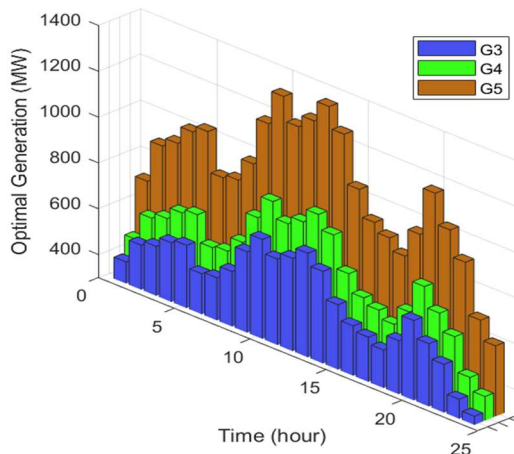


Figure 13 Optimal Participation of area B GENOs in NPS

Likewise, the optimal λ of the area C are 0.0945, 0.133 and 0.1225 for G6, G7 and G8 respectively, which optimally add to the 35% of the generation share, as shown in Figure 14.

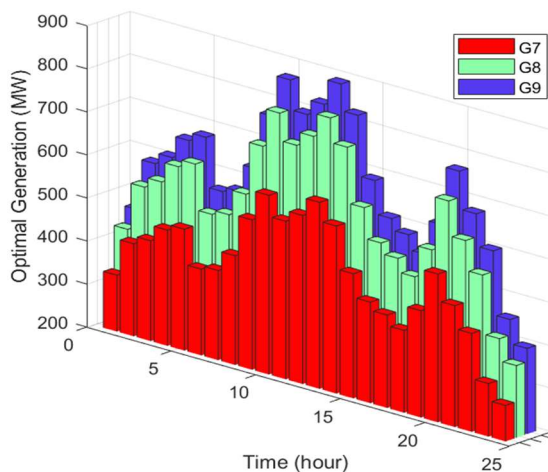


Figure 14 Optimal Participation of GENOS in area C of NPS

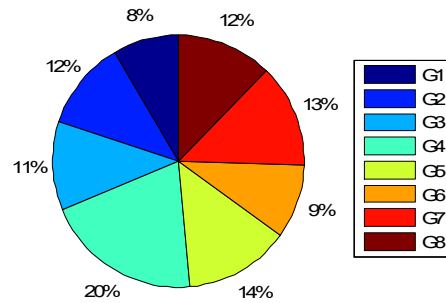


Figure 15 Overall Optimal generation share for the NPS

For instance, at 17:00 hour, 1540 MW (representing 35% of the total hourly demand of 4400 MW) is contracted to area C from DISCOs within and outside the area. The developed ED optimally allocated the generation levels as 415.8 MW, 585.2 MW and 539 MW to G₆, G₇ and G₈ respectively, to meet up with the 1540MW at reduced fuel cost, without violating any the constraints. With these optimal allocations from the developed ED, the overall generation shares from all the 8 GENCOS are as shown in Figure 15.

To demonstrate the superior performance of the developed scheme, the generation cost is compared with those obtained using other various techniques, as summarized in Table 10. From the simulations, it is observed that the fuel costs for GENCOS in area A, B and C are found to be 6.346×10^5 \$/hr, 6.922×10^5 \$/h and 5.961×10^5 \$/hr, adding to up 1.923×10^6 \$/hr, as summarized in Table 10.

Among the techniques used for the comparative analysis, Bat Algorithm obtained the minimal cost of 2.185×10^6 \$/hr, yet not as effective as the developed CSA scheme which obtained the cost of 1.923×10^6 \$/hr, representing 12% reduction.

Table 10 Comparative Analysis on the Fuel Cost

Schemes	Fuel cost (\$) $\times 10^5$			
	Area A	Area B	Area C	TOTAL
MMOHDCM	6.971	7.604	6.548	21.123
CLDE	7.277	7.939	6.837	22.053
HGWMPA	7.567	8.255	7.109	22.931
ImCSO	7.028	7.667	6.603	21.298
IFA	7.724	8.426	7.256	23.406
FSSA	7.310	7.974	6.866	22.150
WOA	7.226	7.883	6.789	21.898
DA	7.296	7.959	6.853	22.108
BA	7.211	7.866	6.773	21.850
Proposed	6.346	6.922	5.961	19.229

As shown in Figure 16, which presents the convergence curves over 100 iterations, the developed scheme not only delivers greater cost reductions but also converges more rapidly than other algorithms. This demonstrates a significant advantage in both efficiency and computational time. The enhanced performance of the CSA is attributed to the careful tuning of the CSA parameters; s , ϑ , μ , and β , summarized in Table 11.

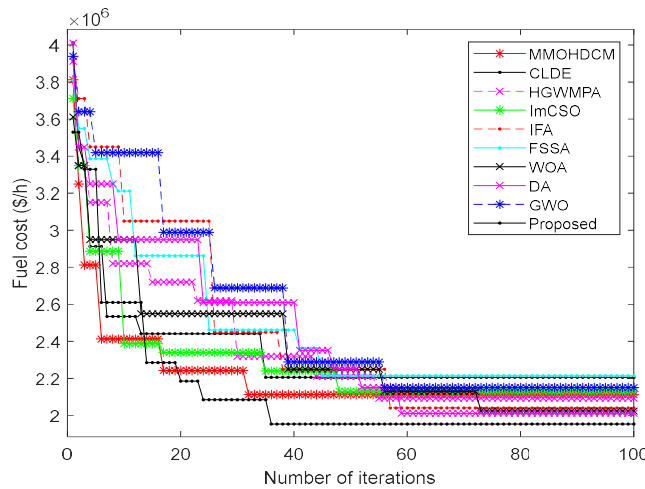


Figure 16 Convergence curves for NPS

Table 11 CSA Parameters

Parameter	Ranges	Value chosen
Step size parameter, σ_u	0.1 – 1	0.52
Lévy Flight Exponent, β	1 – 2	1.47
Scaling Factor, μ	1 – 1.5	1.26
Step angle, ϑ	0.1 – 1	0.82
Number of iterations	---	100

The fuel cost reduction achieved using the developed scheme is largely due to the imposition of the DPM constraint and the use of the CSA. The DPM captures discrete choices made by various market participants (GENCOs and DISCOs), offering a more accurate representation of the market participation. In addition, due to the CSA's ability to strike balance exploration and exploitation in the search space, it efficiently explores the solution space to find optimal solutions.

VI. CONCLUSION

In conclusion, the study developed an optimal scheduling of thermal generators in Multi-Area Power Systems (MAPS), while leveraging the significance of bilateral contracts between DISCOs and GENCOs within or across control areas modelled using DPM. Existing scheduling approaches often overlook these contracts, leading to suboptimal solutions and inefficient resource utilization. To address this, a DPM-constrained optimal scheduling scheme is developed, integrating a matrix capturing each GENCO's participation factors and contractual obligations with DISCOs. This scheduling scheme minimizes fuel costs of thermal generators, incorporating DPM, generation-demand balance, generation limits, and transmission line capacities as constraints. The cuckoo search algorithm is employed due to its rapid convergence, adaptability, and global optimization capabilities to solve this DPM-constrained Economic Dispatch (ED) problem. Implementing this scheme on IEEE 39-bus and 52-bus Nigeria Power System (NPS) partitions into three control areas with multiple DISCOs and GENCOs shows significant fuel cost reductions. Compared to Grey Wolf Optimizer (MOGWO) and Bat Algorithm (BA) solutions, the CSA-based ED showcases

notable improvements—reducing fuel costs by 22.34% for IEEE 39-bus and 20.85% for the NPS. This demonstrated the significance of incorporating the DPM among the constraints and the CSA's superior optimization capabilities in achieving substantial cost savings for the power systems. For future research, dynamic ED problem can be considered for accuracy improvement, instead of static on hourly basis. This will ensure that the optimal generation schedules is computed while considering the changes of parameters such as load demand, generator costs, and system configuration over time.

AUTHOR CONTRIBUTIONS

A. B. Kunya: Conceptualization, problem formulation, and methodological design. **G. S. Shehu:** Software code development, algorithm implementation, and simulation execution. **NSA:** Results analysis, reporting, and manuscript preparation.

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MOPPO
MPC
MRFO
MSA
PIM
PSO
SAMFED
SCSA
SSA
VIU
WOA

Multi-objective proximal policy optimization
Model predictive control
Manta ray foraging optimization algorithm
Membrane Search Algorithm
Power imbalance model
Particle Swarm Optimization
Single-Area Multi-Fuel ED
Self-learning Cuckoo search Algorithm
Squirrel search algorithm
Vertically Integrated Utility
Whale Optimization Algorithm

LIST OF SYMBOLS

F_{ij} Fuel cost
 $p_{G_i}^{max}$ Maximum generation limit
 $p_{G_i}^{min}$ Minimum generation limit
 $P_{G_{ij}}$ Power generation by j th GENCO in i th CA.
 $p_{ij}^{tie-max}$ Maximum tie-line power limit of ij th line
 p_i^{tie} Aggregate power exchange between different CAs
 $\beta_{ij}, \beta_{oi}, \beta_{oo}$ Loss coefficients of the tie-lines.
 \mathcal{J} Number of GENCOs,
 \mathcal{J} Total number of GENCOs
 a_i, b_i , and c_i cost coefficient of i th generator
 e_i and f_i are VPLE cost coefficients of i th generator
 G_i i th GENCO
 L number of tie-lines in the MAPS
 N number of CAs in the MAPS
 β parameter controlling the step size.
 ϑ CSA random variable based on Levy distribution,
 λ_{ij} contract participation factor
 μ CSA scaling factor
 σ_u CSA step size parameter
 ψ total number of DISCOs

LIST OF ABBREVIATIONS

ARMA Autoregressive moving average
CA Control Area
CLDE Comprehensive learning differential evolution
CSA Cuckoo Search Algorithm
CrSA Crow search algorithm
DA Distributed Algorithm
DEFS Differential evolution with fuzzy selection
DISCOs Distribution Companies
DPM DISCO Participation Matrix
ESOA Electro search optimization algorithm
FSSA Fuzzified Squirrel Search Algorithm
GENCOs Generation Companies
GWO Grey wolf optimizer
HDMOMIA Multi objective moth intelligence algorithm
HGWMPA Hybrid grey wolf – Marine Predators Algorithm
HTL-MOPSO Hybrid teaching-learning multi-objective PSO
IFA Improved fireworks algorithm
ImCSO Improved competitive swarm optimization
IPSO Improved PSO
IWM Improved wheeling method
MAED Multi-area economic dispatch
MAMFED Multi-Area Multi-Fuel ED
MMOHDCM Multi-objective hierarchical distributed consensus method
MOGWO Multi-objective grey wolf optimizer