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Solving Economic Load Dispatch Problem Using Grey Wolf Optimization Algorithm

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Abstract: ***This article presents a new evolutionary optimization approach named grey wolf optimization (GWO), which is based on the behavior of grey wolves, for the optimal operating strategy of economic load dispatch (ELD). Nonlinear characteristics of generators like ramp rate limits, valve point discontinuities and prohibited operating zones are considered in the problem. GWO method does not require any information about the gradient of the objective function, while searching for an optimum solution. The GWO algorithm concept appears to be a robust and reliable optimization algorithm is applied to the nonlinear ELD problems. The proposed algorithm is implemented and tested on two test systems having 40 Thermal generators. The results confirm the potential and effectiveness of the proposed algorithm compared to various other methods available in the literature. The outcome is very encouraging and proves that the GWO is a very effective optimization technique for solving various ELD problems.***

Keywords: Economic load dispatch, Valve point effects, Meta-heuristic algorithms, Grey wolf optimization algorithm, and non-convex optimization.

I. INTRODUCTION

Economic load dispatch (ELD) is a process used in power systems to determine the optimal distribution of power output from various generating units to meet the system demand while minimizing the operating costs. This is achieved by optimizing the output of each generator in the system, subject to the operating constraints of the system such as transmission capacity, voltage limits, and stability limits. The ELD problem is a nonlinear optimization problem that requires solving a set of equations to determine the optimal operating point for each generator. The solution is typically obtained using mathematical optimization techniques such as linear programming; nonlinear programming but these mathematical methods are having various disadvantages such as the increased computational complexity of techniques with the size and complexity of the problem. As a result, it may be difficult or even impossible to solve large-scale non convex optimization problems using these techniques. On the other hand, heuristic optimization methods can handle nonlinear and non-convex problems effectively by searching the solution space using a population of solutions and applying evolutionary operators such as mutation, crossover, and selection etc., also ELD problems involve multiple constraints such as power balance, generator output limits, transmission capacity limits, and voltage limits.

Evolutionary algorithm can handle multiple constraints by incorporating penalty functions or constraints handling techniques into the fitness function. In recent literature various heuristic algorithms are reported to solve the ELD problems. Gaing proposed particle swarm optimization (PSO) to solve the ELD problem in power systems and compared with Genetic Algorithm. Several nonlinear characteristics of the generator such as ramp rate limits, POZs and non-smooth cost functions were considered [1]. In [2], Firefly algorithm [FA] was used to determine optimal solution for the ELD problems FA emulates social conduct of fire flies dependent on their blazing quality. Dubey, pandit and panigrahi [3] presented modified flower pollination algorithm [MFPA] to deal the ELD problems. In the MFPA neighborhood fertilization of FPA was constrained by a scaling component and a concentrated exploitation stage was added to determine the best solutions. A continuous version of quick group search optimizer (QGSO) algorithm was proposed to realize me ELD formulation with VPL effect POZs, transformation losses and ramp rate limits [4]. Cuckoo search algorithm (CSA) was developed for solving both convex and non-convex ELD problems [5]. It was inspired from the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds of different species. Simulated annealing technique has been applied to determine the optimal generation schedule for economic dispatch problems in a power system [6]. Hybrid evolutionary programming (HEP) [14] is used to obtain best optimal solution.[7]. In [8] authors used Evolutionary programming method for solving ELD problems .

This paper presents a new swarm based optimization algorithm known as Gray wolf optimization (GWO) developed by proposed by Mirjalili et al. in 2014 [9]. This algorithm is inspired by the hunting nature of the gray wolf. To assess the effectiveness of the GWO, Two test system having different constraints are taken in to consideration and optimized for best optimal fuel cost. Obtained results are compared with the other heuristic methods in the literature.

Organization of this research article as follows: In Section 2, the formulation of the economic load dispatch problem is discussed. In Section 3, the applied Gray wolf optimization algorithm is explained, as well as its implementation process for the ELD problem. In Section 4, Simulation results are presented to compare GWO's effectiveness to that of the original algorithm and other algorithms. Final section summarizes this research work.

II. PROBLEM FORMULATION

The goal of the ELD problem is to find an optimal power generation schedule while minimizing fuel costs and also satisfying the operating constraints of different power systems. The fuel consumption cost of a generator is explained as the following equation.

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \quad (1)$$

Where *a,b,c* are the fuel cost weigh constants. The objective of the ELD problem is to minimize the fuel cost while satisfying equality and inequality constraints

$$minimize(F_T) = \sum_{i=1}^{N} F_i(P_i) \quad (2)$$

Where $F_i(P_i)$ is the fuel cost function of i^{th} unit, P_i is the power output of the i^{th} unit, *N* is the number of generating units in the system. The sequential valve opening in the multivalve steam turbines generates ripple effect on the fuel cost curve of the generator. To model an accurate and practical ELD problem this valve point effect should be included in the fuel cost function as shown in figure 1. Then the fuel cost function of each generating unit is expressed in the non-convex form as follows

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| d_i * sin\left(e_i * \left(P_i^{min} - P_i\right)\right)\right| \quad (3)$$

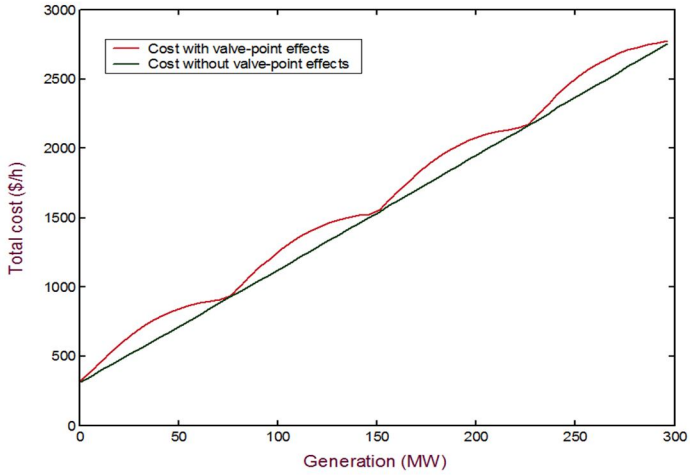

Figure 1 : Fuel cost curve for generators

A. *Power system Constraints*

1) *Power balance constraints*

The generators complete power output must be equal to the sum of power requirement and complete transmission losses and it is provided by the following equations

$$\sum_{i-1}^{N} P_i = P_D + P_L \quad (5)$$

The transmission losses are expresses as

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo} \quad (6)$$

Here P_D is the total load demand and P_L is the system loss. In order to calculate the system loss the method based on penalty factor and constant loss formula coefficient or B coefficient is adopted. B_{ij}, B_{oi}, B_{oo} are the loss coefficient of the generators.

2) Generator capacity Constraints

Each generating unit output power needs to be restricted by limiting inequality between its limits. This constraint is represented by

$$P_i^{min} \le P_i \le P_i^{max} \quad (7)$$

III. GREY WOLF OPTIMIZATION ALGORITHM

Grey wolf optimization (GWO) is a new population based meta-heuristic algorithm proposed by Mirjalili et al. in 2014 [9]. The method imitates the hunting behavior and social hierarchy of grey wolves. On the basis of behavior of grey wolves, GWO is implemented where a specific number of grey wolves in a pack moves through a multi-dimensional search space to look for prey. In this optimization algorithm, the positions of grey wolves are considered as different position variables and the distances of the prey from the grey wolves determine the fitness value of the objective function. The movement of each individual is influenced by four processes, namely searching for prey (exploration), Encircling prey, Hunting, Attacking prey (exploitation).
These operators are briefly explained and mathematically expressed in the following subsection.

A. Searching for Prey (Exploration)

The grey wolves diverge from each other position for searching a victim. Make use of AM with random values to compel the search agent to diverge from the victim. The component CM provides random weights for searching prey in the search space. Hence exploration through AM and CM permits this algorithm to globally search the area. CM vector also presents the effect of obstacles to impending the prey.

B. Encircling Prey

The alpha, beta and delta estimate the position of the three best wolves and other wolves updates their positions using the positions of these three best wolves. Encircling behavior can be represented by DM. The expected boundary is mathematically represented by the following equations:

$$DM = |CM.XP(t) - X(t)| \quad (8)$$

$$X(t+1) = XP(t) - AM.DM \quad (9)$$

Here *t* indicates the current iteration, AM and CM are coefficient vectors, *XP(t)* is the position vector of prey, *X(t)* represents the position vector of a grey wolf. r_1 and r_2 are random vectors in [0, 1].*a* is linearly decreased from 2 to 0.

$$AM = 2a * r_1 - a \quad (10)$$

$$CM = 2 * r_2 \quad (11)$$

C. Hunting

Conservation of regional habitat connectivity has the potential to facilitate recovery of the grey wolf. After encircling, alpha wolf guides for hunting. Later, the delta and beta wolves join in hunting. It is tough to predict about the optimum location of prey. The hunting behavior of grey wolf, based on the position of alpha, beta, gamma (candidate solution) wolf can be represented by

$$DM_\alpha = |CM_\alpha.XP_\alpha(t) + X| \quad (12)$$

$$DM_\beta = |CM_\beta.XP_\beta(t) + X| \quad (13)$$

$$DM_\delta = |CM_\delta.XP_\delta(t) + X| \quad (14)$$

Finally, the position of various categories of wolves is modified as follows:

$$X_{\alpha 1} = X_{\alpha} - AM.DM_{\alpha} \quad (15)$$

$$X_{\beta 1} = X_{\beta} - AM.DM_{\beta} \quad (16)$$

$$X_{\delta 1} = X_{\delta} - AM.DM_{\delta} \quad (17)$$

$$X(t+1) = \frac{X_{\alpha 1} + X_{\beta 1} + X_{\delta 1}}{3} \quad (18)$$

D. Attacking prey (exploitation)

The grey wolves stop the hunting by attacking the prey when it stop moving. It depends on the value of *a* AM* is a random value in the interval [*-2a, 2a*]. In GWO, search agents update their positions based on the location of alpha, beta, delta wolves mentioned in hunting phase and attack towards the prey.

E. Grey wolf optimization applied to ELD

The different steps of GWO algorithm for solving ELD problems are described below.

1) Step 1: Active power generation of all the generating units initialized randomly within their lower and upper real power operating limits

2) Step 2: Evaluate fitness of each solution of current population using (1)–(3). Each fitness value represents the distance of the individual wolf from the prey.

3) Step 3: Sort the population from best to worst. The best, second best and third best solutions respectively, represent the positions of α, β and δ categories of wolves.

4) Step 4: Modify the position of each search agents using the searching prey, encircling prey, hunting and attacking prey concepts. The position of each search agent represents a potential solution comprised of active power generation of ELD problem.

5) Step 5: Check whether the operating limits of the active power of all generating units except last unit are violated or not. If any power generation is less than the minimum level, it is made equal to minimum value. Similarly, if it is greater than the maximum level, it is assigned its maximum value. Subsequently, last unit of the power generation is evaluated using (5) and whether it satisfies all the inequality constraints or not is checked. The infeasible solutions are exchanged by the best feasible solutions.

6) Step 6: Go to Step 2 until termination criteria is met. The GWO is stopped executing when the maximum number of iterations (generations) is reached or there is no noteworthy improvement in the solution. In this paper, the ending criterion is the maximum number of iterations for which most of the grey wolves or search agents are idle.

IV. CASE STUDIES AND NUMERICAL RESULTS

In order to validate the feasibility of the proposed GWO method for the ELD problems, it is employed on a relatively large system consisting of 40 generating units. The load demand used in the simulations is 10500 MW. In order to judge the efficacy of the proposed in nonlinear environment, the valve-point effect and prohibited operating zones are considered. Data for the test system is referred from [10]. The developed algorithm is simulated and tested in MATLAB 7.1 Software on 2 GHz Pentium IV, 1 GB RAM personal computer. The population size and the maximum iteration number are taken as 50 and 500 respectively for the test systems under consideration.

Test Case 1: 40-unit system without valve point loading effect and without Transmission loss.

Test Case 2: 40-unit system including valve point loading effect and Transmission Loss.

A. Test System 1

In this 40 unit test system Valve point effects and Transmission losses are not considered for the simulation. The results obtained by applying the GWO algorithm and other heuristic method known as variable scaling hybrid differential evolution (VSHDE) [11] are summarized in Table 1 for 40-unit power system without considering the effects of valve-point loading without transmission losses. Analyzing the data, it can be observed that the GWO method succeeds in finding a satisfactory solution.

The minimum cost obtained by the proposed GWO method was given by 121244 $/hr, which is the best cost found so far. The analysis of these comparative results demonstrates that the proposed approach shows superior performance compared to other method reported in the literature. Convergence curve for this test system is shown in figure 3.

Table 1 : Best fuel cost Simulation test results for the Test system 1

Unit	GWO	VHSDE	Unit	GWO	VHSDE
1	80	79.63	22	550	550
2	120	119.99	23	550	550
3	190	189.98	24	550	550
4	41.24206	36.27	25	550	550
5	38.08678	42	26	550	550
6	140	140	27	550	549.99
7	300	300	28	10.17545	10
8	300	299.98	29	10.17545	10
9	300	300	30	10.17545	10
10	130	131.97	31	20	20.01
11	94	94.03	32	20	20.01
12	100.7911	94	33	20	20
13	171.2593	174.03	34	20	20
14	339.2156	327.7	35	18	18.01
15	337.9593	339.51	36	18	18
16	337.9593	339.49	37	20	20
17	337.9593	350.34	38	25	25.06
18	500	500	39	25	25
19	500	500	40	25	25
20	550	550	Total Cost (S/hr)	121244	121253
21	550	550			

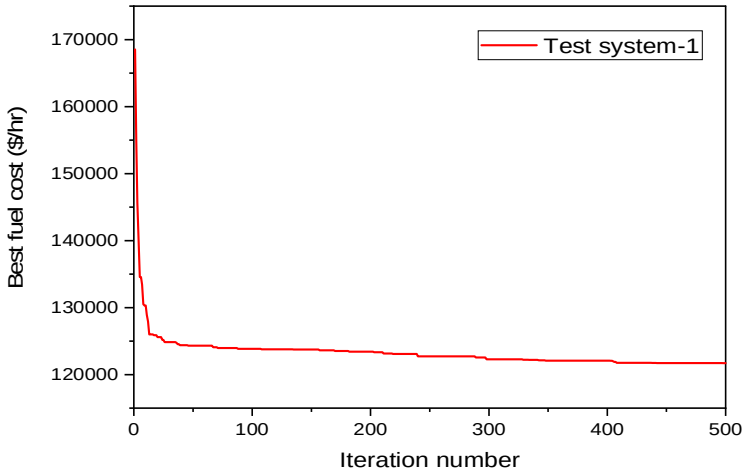

Figure 2 : Convergence curve for the test system-1

B. Test system 2

The simulation results obtained by proposed GWO method for 40- unit test system considering transmission losses and valve point loading effects are compared with GA-API [12],SDE [10],TLBO [13] in Table 2. From Table 2, it was observed that GWO outperforms other optimization methods. In this case, the GWO obtained total cost 2267.8 $/hr, 560.3 $/hr, 217 $/hr lesser than the GA-API, SDE, and TLBO algorithms respectively. Convergence curve for this test system is shown in figure 3. The simulation results clearly suggest that GWO produces feasible solutions. To judge the superiority and robustness,

Table 2 : Best fuel cost Simulation test results for the Test system 1

Unit	GA-API	SDE	TLBO	GWO	Unit	GA-API	SDE	TLBO	GWO
1	114	110.06	114	114	22	550	550	522.1852	523.2794
2	114	112.41	114	114	23	550	550	526.1804	523.2794
3	120	120	120	120	24	550	528.16	521.1967	523.2794
4	190	188.72	182.4448	179.7331	25	550	524.16	525.801	523.2794
5	97	85.91	90.6923	87.7999	26	550	539.1	526.0022	541.3818
6	140	140	140	140	27	11.44	10	13.0804	10
7	300	250.19	300	300	28	11.56	10.37	11.0397	10
8	300	290.68	296.0682	300	29	11.42	10	12.9373	10
9	300	300	288.8518	300	30	97	96.1	89.7412	87.7999
10	205.25	282.01	281.952	279.5997	31	190	185.85	190	190
11	226.3	180.82	238.1293	243.5997	32	190	189.54	190	190
12	204.72	168.74	251.012	243.5997	33	190	189.96	190	190
13	346.48	469.96	483.1175	484.0392	34	200	199.9	200	200
14	434.32	484.17	481.9042	484.0392	35	200	196.25	200	200
15	431.34	487.73	488.2883	484.0392	36	200	185.85	164.7435	164.7998
16	440.22	482.3	396.3448	484.0392	37	110	109.72	110	110
17	500	499.64	494.2577	489.2794	38	110	110	110	110
18	500	411.32	408.3826	489.2794	39	110	95.71	110	110
19	550	510.47	510.5206	511.2794	40	550	532.47	547.9677	511.2794
20	550	542.04	521.2217	511.2794	Total cost ($/hr)	139865	138157.5	137814.2	137597.2
21	550	544.81	540.57	433.5196	Total Loss MW	1045.06	974.43	1002.63	1021.504

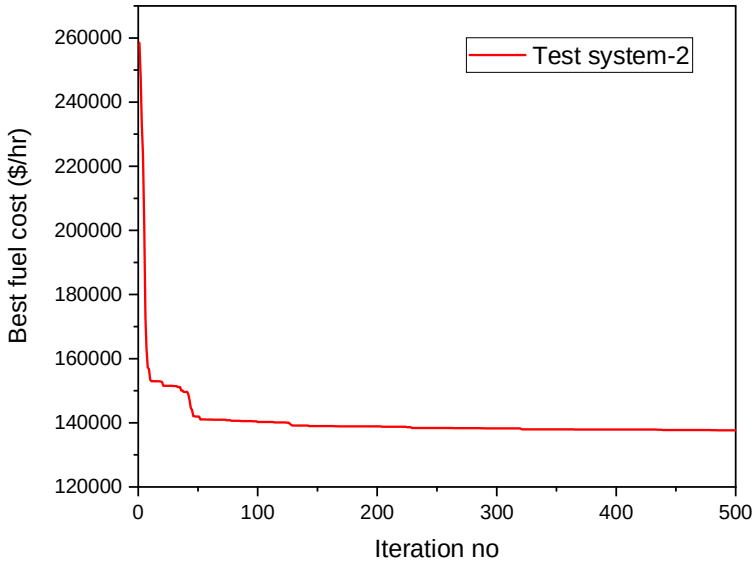

Figure 3 : Convergence curve for Test system-2

V. CONCLUSION

In this work, an efficient meta-heuristic algorithm named GWO is proposed to solve the ELD problem taking the valve point loading effects, prohibited operating zone, ramp rate limits into consideration. Two case studies are employed to demonstrate the applicability of the GWO method. The benefit of the proposed GWO is that it does not impose any convexity limitations on the generating unit characteristics. Numerical results show that the GWO method has superior features, advantages over other algorithms in terms of robustness, avoids premature convergence, simple applicability and stable convergence characteristic. Although, the proposed algorithm is applied to solve ELD problems in the current study, it seems from its unique feature that GWO has the potential to solve many other optimization problems in the field of power system planning and operation.

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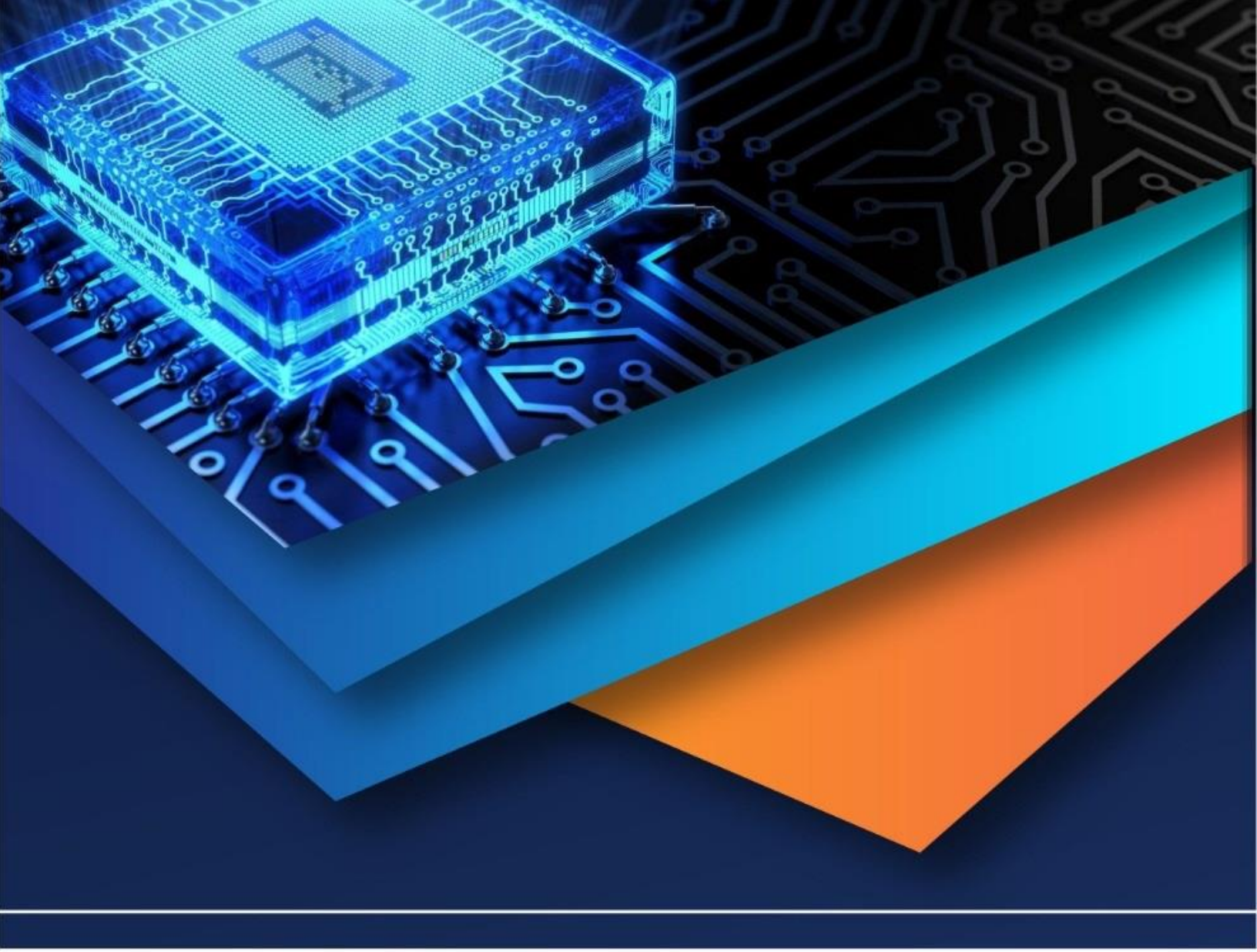

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