Optimal Integration of Multiple Shunt Reactive Compensators in Radial Distribution Systems for Loss Reduction using Modified Mountain Gazelle Optimizer (MMGO)

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Abstract – *This paper proposed a two-step approach for reducing power losses using a Modified Mountain Gazelle Optimizer (MMGO). First, the loss sensitivity factor is used to identify the most promising locations for shunt reactive compensators. This approach reduces the search space and improves the efficiency of the optimization process. Secondly, the proposed MMGO algorithm is applied to determine the optimal locations and sizes of the shunt compensators. The performance of the proposed method is evaluated on standard IEEE 33-bus and IEEE 69-bus systems and compared with other optimization techniques reported in the literature. The proposed MMGO produced 34.05% and 35.45% reductions in active power losses in the IEEE 33 and 69 bus systems respectively. Simulation results demonstrated the effectiveness of the two-step approach in achieving significant loss reduction and improving voltage profiles. The findings of this research provide valuable insights for distribution system operators and pave the way for more efficient and reliable power distribution networks.*

***Keywords**: loss sensitivity factor (LSF), modified mountain gazelle optimizer (MMGO), radial distribution system, shunt reactive compensator, system power losses*

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I. Introduction

The efficient operation of electrical power distribution systems is crucial for minimizing power losses and ensuring reliable power delivery [1]. One of the primary challenges in power distribution systems is to minimize the power losses that occur due to the inherent resistance and high current flows in the distribution lines [2] – [3]. Loss reduction is a critical objective for distribution system operators as it leads to cost savings and increased efficiency [4].

Shunt reactive compensators are a commonly used technique to reduce power losses in distribution networks [5] – [6]. The integration of shunt compensators such as capacitor banks, and D-STATCOMs at strategic locations in the distribution system can improve voltage regulation and reduce power losses [3]. However, the optimal placement and sizing of these compensators is a complex problem due to the non-linearity and non-convexity of the loss reduction function [7].

In recent years, various optimization techniques have been proposed to address the problem of optimal shunt compensator placement and sizing. For instance, the authors in [8] used a hybrid Seagull-Differential Evolutional algorithm to place different types of shunt compensators in distribution networks to reduce losses and improve voltage profile. D-STATCOMs are optimally placed and sized in radial distribution systems in [9] to reduce system power losses using Sine Cosine Algorithm (SCA). Ant Lion Optimization (ALO) algorithm is used in [6] to optimize the integration of a D-STATCOM in IEEE 33-bus radial distribution system for loss reduction and voltage profile improvement. Salah et al [2] placed and sized capacitors, DSTATCOMs, and SVC in radial distribution systems for loss reduction and voltage improvement using the Turbulent Flow of Water Optimization (TFWO) algorithm. Also, Cuckoo Search Algorithm (CSA) has been used to place and size multiple D-STATCOMs in distribution networks to reduce system power losses and improve system voltage profile [10]. Finally, a Whale Optimization Algorithm (WOA) [11] is used to optimize the placement and sizes of capacitors in radial distribution systems to improve the system voltage profile and reduce system power losses. Nature-inspired metaheuristic optimization algorithms have exhibited good prospects in optimizing the integration of shunt compensators to improve power delivery [12]. Further work requires the exploration of more algorithms to enhance the efficiency of power delivery in distribution systems [13] – [15].

In this paper, a two-step approach for reducing power losses using a Modified Mountain Gazelle Optimizer (MMGO). First, a loss sensitivity factor is used to identify the most promising locations for shunt compensators. This approach reduces the search space and improves the efficiency of the optimization process. Secondly, the proposed MMGO algorithm is applied to determine the optimal locations and sizes of the shunt reactive compensators.

The performance of the proposed method is evaluated on standard IEEE 33-bus and IEEE 69-bus radial distribution systems and compared with other optimization techniques in literature, and these include the cuckoo search algorithm (CSA), whale optimization algorithm (WOA), and sine cosine algorithm (SCA).

II. Problem Formulation

A. Loss Sensitivity Factor (LSF)

Optimal locations for the shunt compensators to be installed can be determined using Loss Sensitivity Factors (LSF) [14]. This process reduces the search space and improves the efficient performance of the algorithm for better results. The Loss Sensitivity Factor (LSF) at each bus is derived by differentiating in (1) with respect to the reactive power [10].

$$LSF_{(j)} = \frac{\partial P_{ij(Loss)}}{\partial Q_j} = \frac{2Q_j}{|Vj|^2} \times R_{ij} \qquad (1)$$

LSF for all the buses is calculated using in (1) and then sorted in descending order from the weakest bus to the end. The weaker busses are selected as candidate locations for shunt reactive compensators installation. The final locations and sizes of the shunt reactive compensators are determined using the MMGO algorithm described in the next section.

B. Shunt Reactive Compensator Model

Shunt Reactive Compensators in distribution systems commonly include shunt capacitors, and FACTs devices such as SVC, and D-STATCOM [2]. Each type has its unique strengths and weaknesses, however, they all have the common quality of being shunt-connected and injecting reactive power into the distribution system at the connected bus. Hence, the shunt reactive compensator is modeled as a reactive load but with an opposite sign to represent reactive power injection [8]. For a bus *i* with a connected shunt reactive compensator, it is modeled as shown in (2).

$$Q_{i,new} = Q_i - Q_{Comp} \qquad (2)$$

where $Q_{i,new}$ is the new reactive demand at bus *i* after the compensator is connected, Q_i is the reactive demand at bus *i* without the compensator, and Q_{Comp} is the amount of reactive power produced by the compensator. The reactive power injected by the shunt compensator should be within the minimum and maximum allowable range as define in (3).

$$Q_{comp}^{\min} < Q_{comp} < Q_{comp}^{\max} \qquad (3)$$

C. Backward-Forward Sweep Load Flow

The Backward-Forward Sweep Load Flow technique reported in [16] by Bhavana Jangid and Smarajit Ghosh was adopted to run the load flow test of the standard IEEE 33-bus and IEEE 69-bus radial distribution systems for analysis. It was chosen based on its efficient performance on power distribution systems. This consists of two major steps, and that is the backward sweep involves computing the line current from the end nodes back to the source node and then computing the bus voltages from the source node forward to the end nodes. The bus voltages are assumed 1 p.u at the initialization stage, and these steps are repeated till convergence is achieved.

D. Problem Formulation

In this work, the main focus is to reduce system power losses and improve the system voltage profile by optimally placing shunt reactive compensators. The problem formulation is therefore based on the total active power losses in the system and the voltage deviations. For a given span of a line from bus *i* to bus *j*, the active power loss on the line can be expressed as shown in (4) [10].

$$P_{ij(Loss)} = \frac{\left[P_j\right]^2 + \left[Q_j\right]^2}{\left[V_j\right]^2} \times R_{ij} \qquad (4)$$

where P_j, Q_j, R_{ij}, and V_j represent the active power at bus *j*, the reactive power at bus *j*, the line resistance of the span, and the voltage at bus *j* respectively. If a compensator is connected at bus *j*, $Q_j = Q_{j,new}$ according to (2). The total active power loss of the system is calculated using in (5).

$$P_{TLoss} = \sum_{\substack{1 \le i \le N \\ i \ne j}}^{1 \le j \le N} P_{ij(Loss)} \qquad (5)$$

It is expressed in per unit as follows.

$$f_1 = \frac{P_{TLoss(comp)}}{P_{TLoss(base)}} \qquad (6)$$

where $P_{TLoss(comp)}$ represents total active power losses of the system with the compensation, while $P_{TLoss(base)}$ represents total active power losses of the base system without compensation. Also, the total voltage deviations of the system are expressed in (7) below.

$$VD = \sum_{j=1}^{N} \left| V_{ref} - V_j \right| \qquad (7)$$

Where V_{ref} (reference voltage) is taken as 1p.u and *N* represents the number of busses in the system. The bus voltage should be within the allowable range.

$$V_j^{\min} \le V_j \le V_j^{\max} \qquad (8)$$

The sum of the system bus voltage deviations is expressed in per unit as f_2 in (9).

$$f_2 = \frac{VD_{(comp)}}{VD_{(base)}} \qquad (9)$$

The main objective function is expressed as F_{obj} in (10), consisting of the sum of f_1 and f_2.

$$F_{obj} = \min\left(f_1 + f_2\right) \qquad (10)$$

III. Modified Mountain Gazelle Optimizer (MMGO)

A. Modified Mountain Gazelle Optimizer (MMGO)

The traditional MGO is a recently developed metaheuristic algorithm that mimics the social behavior of mountain gazelles in wildlife. This algorithm is a population-based algorithm that models four different behaviors of the mountain gazelles into mathematical update operators [17]. The algorithm uses these four operators simultaneously to update the problem population in search of better optimal solutions. These four behaviors are Territorial Solitary of Males (TSM), Maternity Herds (MH), Bachelor Male Herds (BMH), and Migration to Search for Food (MSF). To solve the complex placement problem of multiple shunt compensators, an improved version of the original MGO was used. The improved version of the MGO algorithm herein named Modified Mountain Gazelle Optimizer (MMGO), has been developed by the authors in [18] and it has been shown to exhibit superior performance compared to other algorithms. The improvement stems from three key modifications. Firstly, the traditional random approach for generating the initial population in MGO was replaced with a logistic chaotic mapping technique. Secondly, the Territorial Solitary of Males (TSM) was enhanced by introducing a controlling factor, resulting in (11). The value of this controlling factor denoted as β, was determined iteratively during each iteration within the range of 0 to 1, employing a truncation selection technique. Furthermore, to enable a thorough exploration of the search space and maintain effective population divergence for high-dimensional problems, the update operator at the MSF phase was modified in (19). The details are elaborated as follows.

Territorial Solitary of Males (TSM):

Adult male mountain gazelles protect their territories by engaging in a fight with any intruder that poses a threat of taking control of the territory. This defensive mechanism, TSM, is mathematically modeled and this model was modified as in (11).

$$TSM = male_{gazelle} - \beta \times \left| \left(ri_1 \times BH - ri_2 \times X(t) \right) \times F \right| \times Cof_r \qquad (11)$$

where; ri_1 and ri_2 are random integers 1 or 2, $male_{gazelle}$ represents the position vector of the global solution (best male gazelle), and *BH, F,* Cof_r are given in (12), (13), and (14) respectively. Finally, β is a controlling factor introduced to improve the performance of the original mountain gazelle optimizer.

$$BH = X_{ra} \times r_1 + M_{pr} \times r_2, \qquad ra = \left\{\tfrac{N}{3} \ldots N\right\} \tag{12}$$

X_{ra} is a random solution (young male) in the range of ra. M_{pr} is the average number of search agents randomly selected. N is the number of gazelles, and r_1 and r_2 are random values from a range of 0 and 1.

$$F = N_1(D) \times \exp\left(2 - Iter \times \left(\tfrac{2}{MaxIter}\right)\right) \tag{13}$$

N_1 is a random value in the problem dimension determined using a standard distribution, *Iter*, and *MaxIter* represents the iteration counter and the maximum iterations respectively.

$$Cof_i = \begin{cases} (a+1) + r_3, \\ a \times N_2(D), \\ r_4(D), \\ N_3(D) \times N_4(D)^2 \times \cos\left((r_4 \times 2) \times N_3(D)\right), \end{cases} \tag{14}$$

In (14), a is calculated using in (15). also, r_3 and r_4 are random values selected from a range of 0 to 1. N_2, N_3, and N_4 are random numbers in the normal range of the search space and have the problem dimension.

$$a = -1 + Iter \times \left(\frac{-1}{MaxIter}\right) \tag{15}$$

Maternity Herds (MH):

Nursing mother mountain gazelles, just like other mammals, provide immediate protection and grooming to their young ones. This motherly behavior is modeled in (16).

$$MH = \left(BH + Cof_{1,r}\right) + \left(ri_3 \times male_{gazelle} - ri_4 \times X_{rand}\right) \times Cof_{1,r} \tag{16}$$

X_{rand} is a random vector position of a gazelle from the entire population, ri_3 and ri_4 are integers randomly selected from either 1 or 2.

Bachelor Male Herds (BMH):

Young male mountain gazelles upon attaining maturity create their territories, and this involves competing with other males to gain possession of some female gazelles under their territory. This is modeled in (17).

$$BMH = \left(X(t) - D\right) + \left(ri_5 \times male_{gazelle} - ri_6 \times BH\right) \times Cof_r \tag{17}$$

$X(t)$ is the position vector of the gazelle in the current iteration, ri_5, and ri_6 are integers of either 1 or 2. D is determined using in (18), where r_6 is a randomly selected value from a range of 0 to 1.

$$D = \left(|X(t)| + |male_{gazelle}|\right) \times \left(2 \times r_6 - 1\right) \tag{18}$$

Migration in Search of Food (MSF):

As a foraging technique, mountain gazelles feed on leaves and grasses. Mountain gazelles migrate to different locations in search of preferred grasses to feed on. This was remodeled as in (19). It is an improved form of that in the original mountain gazelle optimizer for effective exploration to avoid sub-optimal solution and obtain global solutions.

$$MSF = (ub - lb + 1) \times r_7 + lb \tag{19}$$

where; *lb, and ub* are the lower and upper bounds of the search space respectively, and r_7 is a randomly determined value (0,1).

Algorithm 1: Pseudo-code of MMGO

Inputs: dimension, population size N, and maximum iterations
Output: Gazelle's location and fitness potential

Create a random population, X_i (i=1,2,..N) using a logistic chaotic mapping
Calculate Gazelle's fitness level.
While (the stopping condition is not met) **do**
  for (each Gazelle (X_i)) **do**
    Calculate TSM using modified TSM based on(9)
    Calculate MH using based on (10)
    Calculate BMH using based on (11)
    Calculate MSF using modified MSF in (12)
    Calculate the fitness values of TSM, MH, BMH, and MSF
  end for
Sort the entire population in ascending order according to fitness.
end while
Return $X_{bestGazelle}$, the Best Fitness value.

B. Implementation Steps:

1. Run BFS load flow on the base radial distribution system without compensation.
2. Calculate LSF using in (10), sort in descending order, and select the top n corresponding buses as candidate locations.
3. Connect compensators at the candidate buses

using in (1) and declare in (9) as an objective function for the MMGO algorithm.

4. Initialize random sizes for the compensators using logistic chaotic mapping.
5. Run BFS load flow on the distribution system with the compensators integrated.
6. Implement the MMGO algorithm to update the compensators' sizes till convergence is obtained.
7. The sizes and locations of compensators with a higher impact on system loss reduction are retained as the optimal solution depending on the number intended to be integrated.

IV. Results and Discussion

The proposed MMGO approach is tested on the standard IEEE 33-bus system and the IEEE 69-bus system. The test integrated three compensators to minimize system losses and improve the voltage profile. The test was implemented using MATLAB R2019a software on HP Pavilion laptop with specifications of four (4) gigabytes of RAM, an AMD processor with a clock speed of 2.0 GHZ. The MMGO parameters are set as follows; number of search agents = 30, and maximum iteration = 20.

The IEEE 33-bus system is a radial distribution system with 33 buses and 32 lines, a base voltage of 12.66KV, and 100MVA [10, 11]. It has a total load of 3.72MW and 2.3MVAr, and total active power losses and reactive power losses of 202.67KW and 135.14KVAr respectively. The single diagram of the IEEE 33-bus system is shown in Fig 1.

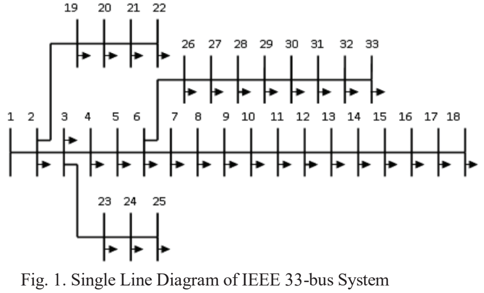

Fig. 1. Single Line Diagram of IEEE 33-bus System

The simulation result from the test on the IEEE 33-bus system is presented in Table I. It captures the compensators' sizes with corresponding locations, total active power losses, the percentage reduction in active power losses, total reactive power losses, the percentage reduction in total reactive power losses, and the minimum bus voltage in the system.

TABLE I
RESULTS OF MMGO APPROACH ON IEEE 33-BUS SYSTEM

IEEE 33-bus	Base Case	Proposed MMGO
SC Size / KVAr (location)	-	538 (7), 289 (13), 850 (30)
Real Power /P Loss, (KW)	202.67	133.67
% P Loss Reduction	-	34.05
Reactive Power (Q) Loss (KVAr)	135.14	89.52
% Q Loss Reduction	-	33.76
Min. Voltage	0.91309	0.9391

From Table I, the results showed the optimal placement of three compensators at buses 7, 13, and 30 with compensation sizes of 538KVAr, 289KVAr, and 850KVAr respectively. It reduced the total active power losses of the system to 133.67 KW, representing a 34.05% reduction, and a total reactive power loss to 89.52KVAr representing a 33.76% reduction. The system voltage profile generally improved with a minimum voltage of 0.9391 p.u as shown in Fg. 2.

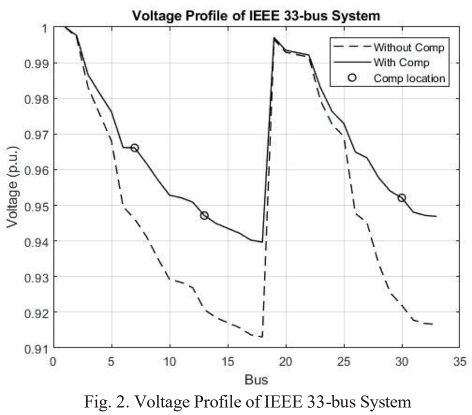

Fig. 2. Voltage Profile of IEEE 33-bus System

To further ascertain the performance of the MMGO approach proposed, a comparison with recent works in the literature on optimal integration of shunt reactive compensators is presented in Table II. It is compared with Cuckoo Search Algorithm (CSA) technique [10], and the Whale Optimization Algorithm (WOA) approach [11].

TABLE II
RESULTS OF MMGO COMPARED WITH OTHER TECHNIQUES

IEEE 33-bus	Base Case	CSA	WOA	Proposed MMGO
SC Size / KVAr (location)	-	350 (14), 520 (24), 1010 (30)	1223 (30), 511 (24), 435 (11)	538 (7), 289 (13), 850 (30)
Real Power /P Loss,(KW)	202.67	138.45	139.81	133.67
% P Loss Reduction	-	31.69	31.02	34.05
Reactive Power (Q) Loss (KVAr)	135.14	93.29	95.41	89.52
% Q Loss Reduction	-	31.00	29.40	33.76
Min. Voltage	0.91309	0.938	0.9315	0.9391

The proposed MMGO approach outperformed the other two methods by producing an active power loss reduction of 34.05% and reactive power loss reduction of 33.76% using a total compensation size of 1,677KVAr. CSA technique produced a 31.69% reduction in total active power losses and a 31% reduction in total reactive power losses using a total compensation size of 1,880KVAr. Also, the WOA approach produced a 31.02% reduction in total active power losses, and a 29.40% reduction in reactive power losses using a total compensation size of 2,169KVAr. The proposed MMGO outperformed the other approaches in literature with a higher amount of percentage reduction in power losses while using less reactive compensation.

The IEEE 69-bus system has also been adopted to test the performance of the proposed MMGO approach. It is a radial distribution system with 69 buses and 68 lines, a base voltage of 12.66KV, and 100MVA. Detailed information on the system is provided in [10]. The single diagram of the IEEE 69-bus system is shown in Fig. 3.

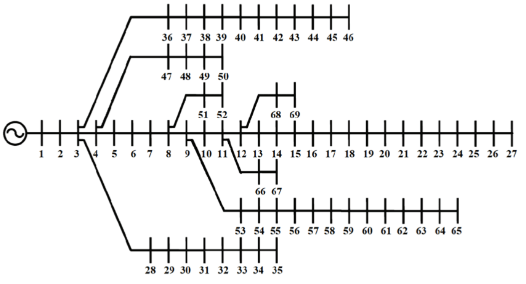

Fig. 3. Single Line Diagram of IEEE 69-bus System

Table III contains the results of the proposed MMGO approach on the IEEE 69-bus system. It is used to place and size three compensators for optimal performance.

TABLE III
RESULTS OF MMGO APPROACH ON IEEE 69-BUS SYSTEM

IEEE 69-bus	Base Case	Proposed MMGO
SC Size / KVAr (location)	-	239 (12), 227 (17), 1244 (61)
Real Power /P Loss, (KW)	225	145.24
% P Loss Reduction	-	35.45
Reactive Power (Q) Loss (KVAr)	102.14	67.71
% Q Loss Reduction	-	33.71
Min. Voltage	0.90919	0.93132

The proposed MMGO approach successfully placed three compensators at bus 12, 17, and 61 with corresponding optimal sizes of 239KVAr, 227KVAr, and 1244KVAr respectively. This effectively reduced the total active power losses of the system to 145.24KW representing a 35.45% reduction, and a total reactive power loss of 67.71KVAr representing a 33.71% reduction. A general voltage profile enhancement with a minimum voltage of 0.93132 p.u has also been obtained as shown in Fig. 4.

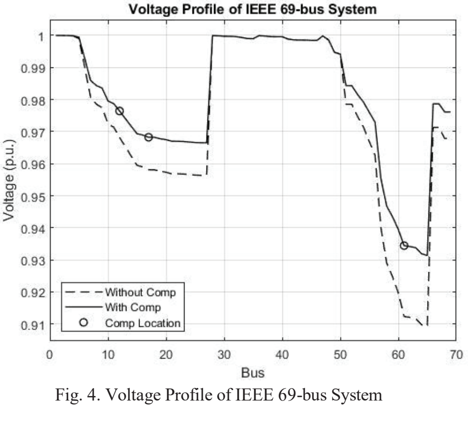

Fig. 4. Voltage Profile of IEEE 69-bus System

To better appreciate the performance of this work, the MMGO approach is compared with the Sine Cosine Algorithm approach in [9], and the Cuckoo Search Algorithm approach proposed in recent research work [10]. The outcome is illustrated in Table IV.

TABLE IV
RESULTS OF MMGO COMPARED WITH OTHER TECHNIQUES

IEEE 69-bus	Base Case	SCA	CSA	Proposed MMGO
SC Size / KVAr (location)	-	226.6 (25), 1078.7 (62), 226.6 (63)	350 (11), 230 (18), 1170 (61)	239 (12), 227 (17), 1244 (61)
Real Power /P Loss, (KW)	225	158.75	145.34	145.24
% P Loss Reduction	-	29.44	35.40	35.45
Reactive Power (Q) Loss (KVAr)	102.14	69.11	67.78	67.71
% Q Loss Reduction	-	32.34	33.64	33.71
Min. Voltage	0.90919	0.9316	0.9301	0.93132

The MMGO approach outperformed the other two techniques by producing a 35.40% reduction in total active power losses and a 33.71% reduction in total reactive power losses using a total reactive compensation of 1,710KVAr. The SCA approach produced a 29.44% reduction in total active power losses, and a 32.34% reduction in total reactive power losses using a total reactive compensation of 1,531.9KVAr. Finally, the CSA approach produced a 35.40% reduction in total active power losses, and a 33.64% reduction in total reactive power losses using a total reactive compensation of 1,750KVAr. It is obvious that the CSA approach produced competitive results, however, the proposed MMGO approach used less amount of reactive compensation to produce the results presented.

V. Conclusion and Recommendation

In this work, a new approach has been proposed to optimally place and size shunt reactive compensators in distribution systems for loss reduction based on the MMGO algorithm. It has been tested on IEEE 33-bus system and IEEE 69-bus system to reduce power losses and improve voltage profiles. The improved algorithm was tested against CSA and WOA algorithms on the IEEE 33 bus system and against CSA and SCA on IEEE 69 bus system. MMGO achieved the highest reduction in active power losses of 34.05% and 35.45% on IEEE 33-bus and IEEE 69-bus respectively. The CSA method which achieved a good result only reduced the active power loss by 31.69% on IEEE 33-bus and 35.40% on IEEE 69-bus. The MMGO outperformed the existing methods to justify the effectiveness of the proposed method. The results achieved by the MMGO method proved itself for the optimal integration of any shunt reactive compensator in a radial distribution system.

The MMGO algorithm is, therefore, recommended for applications in optimization problems in power systems such as optimal integration of distributed generators, optimal placement of sectionalizing switches, and optimal reconfiguration of distribution systems for efficient power delivery.

Conflict of Interest

The authors declare no conflict of interest in the publication process of the research article.

Author Contributions

E. Twumasi conceptualized the research, performed the analysis, and drafted the original paper. A. F. S. Yussif performed the simulation, also involved in the drafting and analysis of the paper and E. A. Frimpong fully supervised the research, reviewed and edited the paper.

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