IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received December 20, 2021, accepted January 10, 2022, date of publication January 18, 2022, date of current version February 3, 2022.
Digital Object Identifier 10.1109/ACCESS.2022.3144065

Investigation of a Multi-Strategy Ensemble Social Group Optimization Algorithm for the Optimization of Energy Management in Electric Vehicles

AALA KALANANDA VAMSI KRISHNA REDDY
AND KOMANAPALLI VENKATA LAKSHMI NARAYANA, (Senior Member, IEEE)
School of Electrical Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu 632014, India
Corresponding author: Komanapalli Venkata Lakshmi Narayana (vlnarayana.k@vit.ac.in)

ABSTRACT A multi-strategy ensemble social group optimization algorithm (ME-SGO) to improve the exploration for complex and composite landscapes through distance-based strategy adaption and success-based parameter adaption while incorporating linear population reduction is proposed. The proposed method is designed to achieve a better balance between exploration and exploitation with minimal tuning while overcoming the limitations of SGO. The proposed improved algorithm is tested and validated through CEC2019's 100-digit competition, five engineering problems and compared against the standard version of SGO, four of its latest variants, five of the advanced state-of-the-art meta-heuristics, five modern meta-heuristics. Furthermore four complex problems on electric vehicle (EV) optimization namely, the optimal power flow problem with EV loading for IEEE 30 bus system (9 Cases) and IEEE 57 bus-system (9 cases) optimal reactive power dispatch with uncertainties in EV loading and intermittencies with PV and Wind energy systems for IEEE 30 bus system (25 scenarios), dynamic EV charging optimization (3 cases) and energy-efficient control of parallel hybrid electric vehicle (3 cases with 2 scenarios) covering the domains of power systems, energy and control optimization have been considered for validation through the proposed multi-strategy ensemble method and fifteen other state-of-the-art advanced and modern algorithms. The performance for the standard engineering problems and the EV optimization problems was excellent with good accuracy of the solutions and least standard deviation rates.

INDEX TERMS Multi-strategy ensemble social group optimization (ME-SGO), social group optimization (SGO), CEC2019, engineering problems, optimal power flow, EV loading, EV optimal control, optimal charging.

I. INTRODUCTION

A. INTRODUCTION TO META-HEURISTICS

Meta-heuristic optimization is a major contributor to problem-solving and operation management and has an envisioned status among researchers and practitioners across various domains. Independent of the gradient information of the problem, meta-heuristics are applicable to both single and multi-objective problems, either continuous or discrete systems with a multitude of decision variables and constraining factors. The quality of solutions through meta-heuristic optimization is reliable and, in most cases, more than satisfactory in terms of efficacy and efficiency with limited computational requirements. Swarm and evolutionary approaches have been the dominant domains of the meta-heuristics with algorithms such as PSO, GA and DE being referred to as the backbone of optimization algorithms. Apart from the aforementioned state-of-the-art, research in the development of optimization algorithms continues to grow rapidly with several novel variants inspired by the various forces in nature (e.g., foraging techniques, social interactions, swarming behaviours etc.) published lately.

Besides the swam and evolutionally meta-heuristics, others such as physics-based optimization algorithms, human behaviour-based optimization algorithms (HBBOAs) have gained popularity across the globe with several publications

The associate editor coordinating the review of this manuscript and approving it for publication was Lei Wang.

found across various domains of engineering, mathematics, computer science, decision sciences, finance and management etc. Amongst them, the growth of HBBOAs have been on the rise since the proposal of Taboo Search Algorithm (TSA) in 1996 [1]. Following it, many others such as Harmony Search (HS) in 2001 [2], Imperialist Competitive Algorithm (ICA) in 2007 [3], Teaching–learning-based optimization (TLBO) in 2011 [4], Social Group Optimization (SGO) in 2016 etc. have been the prominent ones. As mentioned earlier, these paradigms are inspired by the improvisation and interaction of human beings as they deal with complex problems and a few examples are the improvisation of music players, the conquest amongst various empires in a colonial system, knowledge sharing and gaining in a classroom, group counselling, sports tournaments and competitions etc. Simplicity, reliability, efficacy have been the attributes that have attracted many researchers to deploy the HBBOAs as part of their optimization research.

B. IMPROVEMENTS AND ADVANCEMENTS IN META-HEURISTICS

The traversal of the search space is dictated by two inchoate phases, namely, exploration or diversification (often referred to as "*Global Search*") and exploitation or intensification (often referred to as "*Local Search*"). Exploration of a larger area of the search space is often the key to enhancing population diversity lowering the risk of population stagnation which in turn leads to local entrapment and premature convergence. Exploitation on the other hand is essential to accelerate convergence and improve the accuracy of the solutions found so far. To summarize, the perfect balance of the two conflicting aspects of exploration and exploitation is crucial to extract the best possible performance of a meta-heuristic in terms of quality of the solutions, consistency, convergence etc.

In most meta-heuristics, the control of these conflicting aspects is often done through "*algorithm-specific tuning parameters"* or through " *parameter tuning*" in short. Ranging from one parameter to several in number, a precise setting of these parameters is often the backbone to eventuate to a good outcome for the chosen problem. Benchmarking tests and empirical results are the most-employed methods pertinent to achieving the best trade-off as seen in a myriad of works. Other complex and viable methods include F-race tuning, Chess Rating System (CRS-Tuning), REVAC (Relevance Estimation and VAlue Calibration) etc. with integration of chaos theory and versatile tuning operators have been deployed successfully in the literature.

While a smaller number of tuning parameters with simpler tuning is congenial, it can prove ineffectual at times with complex search landscapes and large number of problem dimensions. On the other hand, complexity associated with advanced tuning techniques can be difficult for practitioners all while providing nominal improvements in the outcome. Hence, dynamic and adaptive tuning strategies that can intelligently modify the exploration quality and scale with respect the problem's landscape and dimensions while requiring minimal and basic settings are often implemented in various advanced and modern meta-heuristics.

Other reasons to allude to the lack of a competitive performance are to do with the algorithmic structure, population selection and sorting strategies and excessive dependence on one or few search strategies with little to no adaptive measures to improve the population diversity. Most modern meta-heuristics rely on simpler strategies with the incorporation of the global best solution found so far (often termed as "*Leader*" or "*Gbest*") as a propensity to enhance global search (also accelerating convergence) while the fact that such strategies are one-sided and are often found to drift towards the geometric center of the search landscape. The research article at [5] presents evidence as to how shifted and rotated test functions can prove detrimental to such one-sided search methodologies.

C. MULTI-STRATEGY AND MULTI-POPULATION BASED IMPROVEMENTS

There has been a mammoth of research to improve or enhance the limitations with such search methodologies in the past and the recent literature. Modifying the algorithmic structure to suit the search landscape either for complex benchmarking or domain-specific problems are achieved through a myriad of techniques and hybridization or combination of two or more meta-heuristics for a synergistic boost in the performance have been very popular with researchers from various domains. Likewise, the ensemble techniques integrating multiple meticulously designed and re-forged search strategies with adaptive tuning operators have also contributed to the improvement of the classic paradigms. Additionally, multi-population techniques incorporating a different set of populations with each set governed and dictated by distinguished search techniques have also been popular among the community of optimization.

Performance improvement through the avoidance of local entrapment while staying true to its faster converging nature have been the ultimate goals with such implementations. The other side of the coin is the demerits that accompany them including, increased computational resources, complexity and computational times, a larger number of function evaluations, complexity in implementation owing to the tuning prerequisites for individual search strategies in multi-ensemble techniques, lack of a strong immunity to "*the curse of dimensionality*", very slow convergence rate for simpler problems etc.

Although multi-population ensemble techniques are hailed as the state-of-the-art for a wide range of problems, the tedious coding and tuning of these can be excruciating to the average practitioner. Hence, a balanced approach relying on simpler yet meticulously designed, multiple yet fewer search strategies with lower tuning requisites and adaptive techniques are preferred while standing unabated to the performance in terms of solution quality and convergence.

Literature Survey of the State-of-the-art Multi-Strategy and Multi-Population Based Improved Algorithms: A literature survey of the most-cited multi-strategy and multi-population based improved meta-heuristics is presented below.

1) GA BASED ENSEMBLE ALGORITHMS

(i) A two-stage multi-population genetic algorithm (MPGA) was proposed by Cochran *et al.* [6] in 2003 incorporating sub-population evolution and elitism to optimize parallel machine scheduling problems. MPGA outperformed MOGA for scheduling problems with two and three objectives with a higher number of Pareto Front solutions with better solution quality although the limitation that both the algorithms produced unwanted solutions dominated by others was acknowledged. (ii) A novel multi-strategy ensemble ABC (MEABC) algorithm, the coexistence and competition between pools of distinct solution search strategies i.e., The original ABC, GABC and Modified ABC/best/1 is realized [7]. Benchmarking through 12 commonly used functions and the CEC2013 test suited is utilized while comparisons with the state-of-the-art variants of PSO, DE and ABC are made to demonstrate the effectiveness of MEABC. (iii) An adaptive collaborative optimization algorithm integrating GA's exploration prowess and ACO's stochastic abilities in a multi-population strategy known as MGACACO is proposed [8]. Various scale travelling salesman problems (TSP) are considered to verify the proposed approach. The proposed method outperformed the parent algorithms with better accuracy and fast convergence while avoiding local optima.

2) PSO BASED ENSEMBLE ALGORITHMS

(i) A multiagent-based Particle Swarm Optimization (MAPSO) for optimal reactive power dispatch integrating lattice-based agent-agent interactions and knowledge-based learning to improve optimality and accelerate convergence has been proposed in [9]. MAPSO outperformed SGA and PSO at lowering the active power losses with lower executions times compared to the latter. (ii) Multi-strategy ensemble particle swarm optimization was proposed in 2008 by Du and Li [10]. MEPSO categorizes the particles into two parts with Gaussian local search and differential mutation guiding them to accelerate convergence and prevent local entrapment respectively. Experimental analysis with the moving peaks benchmark (MPB) and dynamic Rastrigin functions demonstrated the effectiveness of MEPSO at evading entrapment compared to other variants of PSO. (iii) Wang *et al.* proposed the Self-adaptive learning-based particle swarm optimization (SLPSO) in [11] with four PSO strategies with a self-adaptive probability model based on the fitness landscapes. Extensive comparisons with eight state-of-the-art variants of PSO for 26 numerical optimization problems and economic load dispatch problem of power systems (ELD) are performed with SLPSO being the top-performer. (iv) In 2013, Diversity enhanced particle swarm optimization with neighbourhood search (DNSPSO) was proposed [12]. To achieve a better trade-off between exploration and exploitation, diversity enhancing mechanism and neighbour search with local and global search systems are integrated and evaluated using 15 standard benchmark functions, CEC2005 and CEC2010 test suites. The proposed method was successful with the least mean errors compared to the variants of PSO. (v) A quantum-behaved particle swarm optimization algorithm incorporating flexible single-/multi-population strategy and multi-stage perturbation strategy (QPSO_FM) to balance the diversity and the convergent speed is proposed in [13]. Benchmarking with 28 standard benchmark functions with several other quantum variants of PSO demonstrated its effectiveness at providing an accelerated global search.

3) DE BASED ENSEMBLE ALGORITHMS

(i) Neighbourhood mutation strategy integrated with various niching differential evolution (DE) algorithms (NCDE) was investigated by Qu *et al.* [14]. Euclidean neighbourhood-based mutation improved the performance for multi-modal landscapes tested against (14 basic multi-modal and 15 composite multimodal problems). (ii) Multi-population ensemble DE (MPEDE) with three mutation strategies and population pools incorporating a dynamic allocation of fitness evaluations to the best strategy has been proposed by Wu *et al.* [15]. Control parameter adaption for each mutation strategy is integrated as well and the improved performance is demonstrated against the CEC2005 test suite comparing several variants of DE. (iii) Ensemble of differential evolution variants (EDEV) incorporating JADE, CoDE and EPSDE with three indicator sub populations and one reward sub population was proposed by Wu *et al.* [16]. EDEV outperformed several variants of DE for the CEC2005 and CEC2014 test suites.

4) OTHER ENSEMBLE ALGORITHMS

(i) In 2005, a restart-Covariance Matrix Adaptation Evolution Strategy (CMA-ES) with restart strategy incorporating increments to the population size (IPOP) known as IPOP-CMA-ES has been proposed by Auger *et al.* [17]. CEC2005 real-parameter optimization test suite with 25 functions were chosen in a benchmarking analysis with the proposed method outperforming the local restart strategy in 29 out of 60 cases. (ii) An Improved Ant Colony Optimization Algorithm Based on Hybrid Strategies (ICMPACO) for TSP and actual gate assignment problem is realized in [18]. The proposed multi-population approach includes co-evolution mechanisms with pheromone updating and diffusion mechanisms for better exploration-exploitation balance and achieved better assignment results. (iii) Multi-population differential evolution-assisted Harris hawks optimization with chaos strategy (CMDHHO) to avoid local entrapment has been realized in [19]. In a comparative analysis with several modern and advanced meta-heuristics with CEC2017 and CEC2011 (selected functions for real-world issues) test suites, CDMHHO outperformed them. (iv) Chaotic multi-swarm whale optimizer (CMWOA) by Wang and Chen [20] for support vector machine-based medical diagnosis combining chaotic and multi-swarm strategies is proposed. In a comparative analysis against PSO, BFA and PSO, the proposed method achieved better classification performance and feature subset size. (v) A multi-strategy ensemble GWO (MEGWO) with an enhanced global-best lead strategy to improve local search and an adaptable cooperative strategy to promote global search and population diversity is proposed in [21]. 30 benchmark test problems from the CEC2014 suite are chosen for the benchmarking and 12 feature selection datasets are considered. In a comprehensive comparison with various meta-heuristics, MEGWO showcased robust optimization results for both benchmarking and feature selection.

A brief summary of the aforementioned publications considered for the literature survey has been tabulated in Table 27 (**Appendix**)

D. CONTRIBUTIONS OF THE CURRENT ARTICLE

Following the literature survey of the state-of-the-art, the current article proposes a multi-strategy ensemble social group optimization (ME-SGO) algorithm to improve the performance of the standard social group optimization (SGO) for complex and composite landscapes and an investigation of its performance for complex multi-dimensional, non-linear, multi-constrained problems on the optimization of electric vehicles from the recent literature is made. The reasons for the choice of SGO as the optimizer to be improved and the selection of the four problems on EV optimization are listed in the following sub-sections.

1) CHOICE OF SGO

The following have been the factors for the choice of SGO over other contemporary meta-heuristics.

1) SGO is a relatively new meta-heuristic proposed in 2016 with a simple structure and can be implemented on multiple programming languages with support for parallel computation and black-box mode of implementation.
2) The performance of SGO for unimodal and multimodal landscapes has been outstanding as it outperformed several state-of-the-art variants of DE, PSO, ABC in recent publications 22]–[25].
3) There exists a huge potential to improve and enhance the exploration of SGO through multiple strategies with a wide range of parameter adaptation techniques for composite and hybrid search landscapes where it is known to struggle.
4) Although a few improved and hybrid variants of SGO exist in the recent literature, none of them have demonstrated the improved performance for complex and composite landscapes. This has been the centre of focus in the current manuscript.
5) Very little effort has been made to improve the performance of SGO through dynamic and adaptive parameters that control its search process (population size, social introspection factor).
6) Efforts made to improve SGO through the enhancement of population diversity have not been comprehensively verified with other state-of-the-art advanced meta-heuristics for complex and real-world optimization problems.

Hence based on the aforementioned aspects, the proposed multi-strategy ensemble variant of SGO aims to deliver a better balance of exploration and exploitation for complex real-world problems especially for complex and composite landscapes with a higher degree of robustness and precision.

2) OPTIMIZATION IN EV'S

The testing and validation of advanced meta-heuristics are often performed through real-world multi-constrained problems known to be complex and computationally expensive as they help evaluate their overall performance concerning limited computational resources, high dimensionality and high-multimodality with a larger degree of complexity in exploring its dynamic search landscapes. Besides these, a higher number of equality and inequity constraints often restrict the algorithm from exploring the landscapes to their fullest potential which is often the case with static control parameters. In this regard, four complex problems on EV optimization covering the areas of power systems, energy management and control optimization from the recent literature are chosen to demonstrate yeh the performance potential of the proposed method. The following are the reasons for their choice.

1) Electric vehicles have emerged as the next milestone in the transportation sector and have been the centre of focus for research and development over the last decade. More often, the problems on EV optimization are modelled as optimization problems (Linear programming, non-linear programming, integer programming, mixed-integer non-linear programming, convex programming etc.) and solved through various meta-heuristics and solvers. Optimization through meta-heuristics has been the choice on-the-go for many researchers and practitioners on this topic.
2) Most EV optimization problems follow complex mathematical modelling with multiple equality and inequity constraints with a large number of non-separable problems dimensions covering multiple areas of power systems, control optimization, design and energy management with complex landscapes requiring dynamic optimization strategies to ensure better optimality.
3) The integration of machine learning and predictive control techniques can be efficiently coupled with optimization techniques to lower the learning errors paving way for truly autonomous driving and cruise control etc.
4) The design and management of EVs is one such area which requires the collaborative co-optimization of rule-based control and optimization of energy management to work in synergy to ensure optimal driving efficiency.

5) Path finding, EV routing, optimal charging and discharging, optimal planning of EV charging location and charging infrastructure etc. are the best examples that require robust and dynamic optimization techniques to determine the optimal solution as the scope of these areas tends to expand.

Over the last decade, the optimization in very domains concerning EVs have been dominated by the improved/hybrid meta-heuristics indicating the efficiency of adaptive techniques over the classical paradigms. A brief literature survey depicting the development of various improved and advanced meta-heuristics to the very domains of EV optimization is presented in Table 28 (**Appendix**)

Considering the following aspects, four complex problems namely, the optimal power flow problem with EV loading for IEEE 30 bus system (9 Cases) and IEEE 57 bus-system (9 cases) optimal reactive power dispatch with uncertainties in EV loading and intermittencies with PV and Wind energy systems for IEEE 30 bus system (25 scenarios), dynamic EV charging optimization (3 cases) and energy-efficient control of parallel hybrid electric vehicle (3 cases with 2 scenarios) coverage the domains of power systems, energy and control optimization have been considered for validation through the proposed multi-strategy ensemble method and fifteen other state-of-the-art advanced and modern algorithms.

3) ORGANIZATION OF THE ARTICLE

The remainder of this article is organized as follows. Section II focuses on the literature review and working of SGO, review of its variants followed by a discussion of its merits and demerits. Section III discusses the formulation of the multi-strategy ensemble SGO technique with a detailed description of its various attributes. The performance of ME-SGO with fifteen different meta-heuristics (including four variants of SGO, four modern meta-heuristics, and seven state-of the art advanced meta-heuristics) is analysed in Section IV with CEC 2019 benchmark suite and the 100-digit competition followed by a comparative analysis on standard engineering problems (pressure vessel design, welded beam design optimization, tension/compression spring design optimization, cantilever beam design and design of 10-bar truss optimization). Section V analyses the performance of the proposed method and the fifteen competitor algorithms on the four and real-world constrained complex EV optimization tasks The conclusion, followed by the merits and demerits of ME-SGO, potential applications and the future scope of the current work are given in Section VI.

II. SOCIAL GROUP OPTIMIZATION

Social Group Optimization (SGO) is a human behaviour inspired evolutionary technique, proposed by Suresh Satapathy and Anima Naik in 2016 [26]. The inspiration of SGO stems from the social behaviour of human beings collectively working together to solve complex problems. The following sections explain the working of SGO, various attributes of SGO, merits and demerits followed by a detailed literature review of the algorithm including its variants.

A. WORKING OF SGO

SGO is implemented in two phases, namely, the improving phase and the acquiring phase. Both the phases rely on simple evolutionary equations to transform the solutions obtained through random initialization at the beginning following a greedy selection strategy. The search process commences with the identification of the "*leader*" or "*gbest*" from the randomly initiated population pool.

1) IMPROVING PHASE

The "*leader*" influences the population members and propagates his knowledge resulting in the repositioning of the population pool with reference to the "*leader*". The new positions of the population pool are updated as described by (1).

$$\begin{aligned} &\textit{For } \boldsymbol{i = 1 \text{ to } N} \\ &\quad \textit{For } \boldsymbol{j = 1 \text{ to } D} \\ &\quad\quad \vec{\boldsymbol{P}}_{\boldsymbol{i,j}}^{\boldsymbol{(t+1)}} = \boldsymbol{c} \times \vec{\boldsymbol{P}}_{\boldsymbol{i,j}}^{\boldsymbol{(t)}} + \boldsymbol{r} \times \left[\boldsymbol{Leader_j} - \vec{\boldsymbol{P}}_{\boldsymbol{i,j}}^{\boldsymbol{(t)}}\right] \\ &\quad \textit{end for} \\ &\textit{end for} \end{aligned} \tag{1}$$

where,

N stands for the population size, D stands for the number of problem dimensions, t stands for the current iteration, r is a random number in [0, 1] and $r \sim U\,(0,1)$, 'c' is the *self-introspection factor* whose value can be set with the range $0 < c < 1$.

2) ACQUIRING PHASE

Contrary to the improving phase, the acquiring phase is intended for the interaction of the members in the population pool with the leader and other random population members. The interaction is conditional with the person having a greater knowledge transferring his/her knowledge to the other person while a person with lesser knowledge acquires it from a higher knowledgeable person. Since the leader of the social group interacts with every other population member, he/she has the greatest influence on the others to learn from him/her. The new positions of the population pool are updated as described by (2) and (3):

For $\boldsymbol{i = 1 \text{ to } N}$

Randomly select a member $\boldsymbol{P_r}$ *from the population pool such that* $\boldsymbol{i \neq r}$

$$\begin{aligned} &\textit{If } f(\boldsymbol{P_i}) < f(\boldsymbol{P_r}) \\ &\quad \textit{For } \boldsymbol{j = 1 \text{ to } D} \\ &\quad\quad \vec{\boldsymbol{P}}_{\boldsymbol{i,j}}^{\boldsymbol{(t+1)}} = \vec{\boldsymbol{P}}_{\boldsymbol{i,j}}^{\boldsymbol{(t)}} + \boldsymbol{r_1} \times \left[\vec{\boldsymbol{P}}_{\boldsymbol{i,j}}^{\boldsymbol{(t)}} - \vec{\boldsymbol{P}}_{\boldsymbol{r,j}}^{\boldsymbol{(t)}}\right] + \boldsymbol{r_2} \\ &\quad\quad\quad \times \left[\boldsymbol{Leader_j} - \vec{\boldsymbol{P}}_{\boldsymbol{i,j}}^{\boldsymbol{(t)}}\right] \end{aligned} \tag{2}$$

TABLE 1. Tabulation of the merits and demerits of SGO.

Merits	Demerits
Simpler and straightforward to code and can be implemented across a wide range of programming languages.	Although Double Fitness Evalutions per iteration (DFEs) improve the search behaviour, they can lead to a compromise in the population size or iterations under fixed computational requirements.
SGO is excellent for unimodal, most multi-modal and constrained search landscapes (continuous and discrete) with a faster convergence rate to the global optimal solution.	The excessive dependence on the leader can lead to local entrapment in complex search landscapes. This coupled with greedy selection is more likely to cause population stagnation resulting in premature convergence.
Smaller number of tuning requisites, i.e., one algorithm-specific tuning parameter (*self-introspection factor 'c'*) makes it easier to regulate the explorative behaviour for a wide range of problems.	The tendency of the search mechanism to slide to the geometric centre of the search landscape can be detrimental for rotated and shifted landscapes.
Good immunity to the curse of dimensionality and excellent for global search with the greedy selection process updating the population twice in every iteration.	The lack of any adaptive measures can result in the greedy selection limiting the population diversity in complex multi-modal problems.
The modules in the algorithm can be hybridized with other meta-heuristics.	The implementation of the improving phase for the entire population can result in a loss of diversity by concentrating a larger section of the population closer to the *gbest*. This is followed by the acquiring phase for all the population members leading to shallow exploitation of the search space.
Rapid convergence to global optimum for separable benchmark function due to its strong exploitative capabilities.	The empirical setting of the *self-introspection factor* may not be suitable at all times. Improper setting can lead to the fitness evaluations being futile and render the search process useless at times.
	Parallel computational techniques cannot be implemented to efficiently distribute the computational tasks in multi-core machines due to the limitation of the search process.
	A sudden transition from exploration to exploitation witnessed for non-separable benchmark functions indicates a higher probability of local stagnation brought upon by the constriction of the available search space due to limited population movement throughout exploration.

end for

Else

For $\boldsymbol{j = 1 \text{ to } D}$

$$\boldsymbol{\vec{P}^{(t+1)}_{i,j} = \vec{P}^{(t)}_{i,j} + r_1 \times \left[\vec{P}^{(t)}_{r,j} - \vec{P}^{(t)}_{i,j}\right] + r_2 \times \left[Leader_j - \vec{P}^{(t)}_{i,j}\right]} \tag{3}$$

end for

end if

where,

r_1 and r_2 are two random numbers in [0, 1] and $r_1, r_2 \sim U(0,1)$.

Merits and Demerits of SGO: Table 1 lists the merits and demerits of SGO based on a comprehensive literature survey.

B. ANALYSIS AND DEDUCTIONS FROM THE PREVIOUS PUBLICATIONS AIMED AT IMPROVING SGO

Following the proposal of SGO in 2016, several improved variants of SGO have been found in the literature. Exploring the literature, three improved variants, three hybrid variants, one modified and one discreet variant of SGO were found. A deeper analysis of these variants indicates that research into improving SGO has been aimed at enhancing the population diversity to help evade local entrapment. A brief discussion of the variants is given below.

1) Improved SGO (ISGO-Variant 1) based Support Vector Machine (SVM) classifier for transformer fault diagnosis model using an optimal hybrid dissolved gas analysis features subset was proposed by Fang *et al.* [27]. The proposed method aimed at the prevention of local entrapment in SGO through the incorporation of population sub-grouping and eliminating phase to enhance the explorative potential. The proposed method recorded better fitness compared to GA, PSO and SGO based classifiers.
2) In [28], Cluster Head Multi-Hop Routing Algorithm based on another Improved SGO (ISGO-Variant 2) was proposed. The authors proposed a three stage Improved SGO with historical population memory and a ranking system followed by the initial 25 percent of the population learning from the last 25 percent of population. Intended at improving the population diversity, the proposed ISGO outperformed the competitor algorithms for maximizing the network life cycle and minimizing the energy consumption.
3) In other works, Improved SGO (ISGO-Variant 3) for short-term hydrothermal scheduling by Akash *et al.* was proposed [29]. It expands the concept of a self-awareness probability (SAP) factor from MSGO [30] to improve the diversity through re-initialization of the population in the acquiring phase. It performed competitively with lower production costs compared to the competitors in four cases tested.
4) Modified SGO (MSGO-Variant 1) was proposed by Naik *et al.* [30]. A novel modification to the acquiring phase known through the addition a new control parameter known as self-awareness probability (SAP) to enhance the exploratory capabilities with increased population diversity is realized and uses the re-initialization of the solution vector to achieve this. In an extensive benchmarking analysis with 23 classical functions and 3 cases of hydrothermal scheduling problems, MSGO outperformed several classical and contemporary meta-heuristics. Following it in 2021, the same MSGO for circular antenna array optimization was proposed in [31] where MSGO outperformed the classical SGO in terms of optimality, accuracy, convergence and robustness across three cases.

TABLE 2. Summarization of the variants of SGO from the literature.

S. No	Authors and Year	Name of the variant	Categorization	Formulation	NFEs	Application / Benchmarking	Improvement in the performance
01.	J. Fang et al. in 2018 [27]	ISGO	Improved Variant	Population sub grouping and elimination of the weakest	$Np+2\times(Np\times T)$	SVM-based Transformer Fault Diagnosis Model	ISGO outperformed PSO, GA and SGO for five test cases.
02.	Y. Liu et al. in 2018 [28]	ISGO	Improved Variant	Historical population memory with ranking methodology and population learning	$Np+3\times(Np\times T)$	Cluster Head Multi-Hop Routing	ISOG achieved the least energy consumption and maximum network life cycle.
03.	A. Gautam et al. in 2021 [29]	ISGO	Improved Variant	Self-awareness probability (SAP) factor-based population re-initialization in the acquiring phase	$Np+2\times(Np\times T)$	Short-term hydrothermal scheduling	ISGO had lower production costs compared to the competitor in four cases tested
04.	A. Naik et al in 2020 [30]	MSGO	Modified Variant	Self-awareness probability (SAP) factor-based population re-initialization in the acquiring phase	$Np+2\times(Np\times T)$	Benchmarking analysis with 23 classical functions and 3 cases of hydrothermal scheduling problems	MSGO performed competitively throughout the testing
05.	K.V.L. Narayana et al. in 2020 [32]	HS-WOA	Hybrid Variant	Hybridization of WOA with SGO with a modified acquiring phase	$Np+(Np\times T)$	Benchmarking analysis with 30 functions and eight cases of production planning problem	HS-WOA demonstrated faster convergence and better exploitation.
05.	K.V.L. Narayana et al. in 2020 [32]	HS-WOA+	Hybrid Variant	Improving and acquiring phases are combined with bubble-net foraging from WOA	$Np+2\times(Np\times T)$	Benchmarking analysis with 30 functions and eight cases of production planning problem	A better balance of exploration and exploitation was achieved.
06.	A.K. Singh et al. in 2021 [33]	HSGO	Hybrid Variant	A new mutation phase is incorporated into SGO	$Np+3\times(Np\times T)$	COVID-19 infection detection from chest X-Ray images	HSGO based SVM classifier achieved an accuracy of 99.65%
07.	S. Verma et al. in 2020 [34]	DSGO	Discrete Variant	Discretized adaptation of SGO	$Np+2\times(Np\times T)$	Travelling Salesman Problem (5 Cases)	DSGO achieved minimal costs for five TSP datasets with fast convergence
08.	J. J. Jena et al. in 2021 [23]	SGOSAIW	Comparison study	Analysis of the various inertia weight strategies to tune the *self-introspection factor*	$Np+2\times(Np\times T)$	27 benchmark functions suite and a few mechanical and chemical engineering problems	Sigmoid-adaptive inertia weight based SGO obtained better results
09.	A. Naik et al. in 2020 [22]	SGO	Comparison study	SGO was compared with multiple meta-ehuritcs	$Np+2\times(Np\times T)$	A comparative study with multiple classical benchmark functions, CEC special session functions, and six classical engineering problems	SGO had a very competitive performance

5) The hybridization of SGO and Whale Optimization Algorithm (WOA), another popular contemporary swarm-based meta-heuristic to realize two hybrid variants were developed by K.V.L Narayana *et al.* in [32]. A lite version named HS-WOA to improve the exploitation and convergence speeds through a modified acquiring phase with SFEs and an extended version (HS-WOA+) with DFEs to improve the exploration-exploitation balance was proposed. Extensive comparisons with recent and classical paradigms for 30 benchmarking, 4 engineering problems and a multi-unit production planning were carried out to demonstrate the effectiveness of the proposed methods with HS-WOA+'s performance being good for most of the testing.
6) In other developments, a hybrid of SGO and GA, known as HSGO [33] incorporating a new mutation phase into SGO to facilitate continuous improvement in the population is proposed. Deployed to detect COVID-19 Infection from chest X-Ray images, the HSGO based SVM classifier achieved an accuracy of 99.65% among all classifiers outperforming them.
7) A discretized adaptation of SGO known as DSGO to solve the popular Travelling Salesman Problem (TSP) was proposed in ()[34]. Compared to GA and DPSO, DSGO achieved minimal costs for five TSP datasets while demonstrating accelerated convergence.

Following them were two comparative studies at [22] comparing SGO with recent algorithms from 2017 to 2019 for multiple classical benchmark functions while the analysis at [23] investigated the adaptive tuning mechanisms for the self-introspection parameter for solving engineering design problems.

A brief description of the variants of SGO is summarized in Table 2.

A detailed description of the aforementioned variants of SGO is described in Table 29 (**Appendix**).

III. PROPOSED METHOD: MULTI-STRATEGY ENSEMBLE SOCIAL GROUP OPTIMIZATION (ME-SGO) WITH LINEAR POPULATION REDUCTION TECHNIQUE

The proposed multi-strategy ensemble social group optimization aims to deliver a good balance between the exploration and exploitation while ensuring that local entrapment is avoided. Hence, to improve the population diversity and enhance the search capabilities, multiple strategies are designed and integrated systematically to keep track that the algorithm aims for global search. A detailed explanation is provided the following sub sections.

A. MOTIVATION

After a careful analysis of the various works aimed at improving the standard SGO algorithm, the motivation for the current work is as follows:

1) SGO lacks population diversity since the improving phase and acquiring phase are implemented for the entire population and not for individual population members. This system where both the phases rely on greedy selection and as the population pool enters the acquiring phase, very little room exists for further improvement casing clustering leading to local entrapment.
2) The improvement phase requires additional modifications to dynamically adapt to complex landscapes through strategic search equations to improve diversity. A reason to modify improving phase is to ensure that all the population members are not drawn too close to the leader and prevent the of the function evaluations being futile.
3) The static nature of the *self-introspection factor* from the improving phase is another aspect that can drive the nature of the search process. Furthermore, a dynamically adaptive *self-introspection factor* 'c' can significantly improve the exploration during the improving phase.
4) The acquiring phase, although provides ample comparisons among the population can be modified to target the movement of the population towards a global optimum through its immediate implementation after the improving phase for every population member rather than in groups. This way, every population member from the improving phase gets an opportunity to interact with either a random improved solution or one with no improvement preserving population diversity.
5) SGO's adaptation of double fitness evaluations requires either the population size or the iteration count to be lowered to match the required NFEs compared to other modern optimizers with single fitness evaluations. Gradual population reduction schemes can be experimented with in this regard to ensure a higher initial setting for the population size and iterations ensuring a better balance of exploration and exploitation.
6) SGO is excellent at local search providing accelerated convergence to the obtained local optimum points and this ability of SGO can be exploited and further enhanced through modifications to both the improving and acquiring phases.

Following the aforementioned aspects, the following modifications and improvements have been considered in the current work.

1) To adapt to dynamic and complex landscapes, the proposed ME-SGO incorporates dynamically adaptive features incorporated into the improving phase, acquiring phase, population size and the *self-introspection factor*. The complexity of the search landscapes dictates the adaptive rate of these strategies and parameters.
2) To prevent loss of diversity and improve the successful utilization of the function evaluations, the improving and acquiring phases are implemented for every individual population member in an iteration as opposed to the implementation in groups.
3) The improving phase is given a major overhaul with distance-based strategy adaption and success-based control parameter adaption. The distance-based strategy adaption splits the improving phase into two sub-phases each triggered by a pre-set number of function evaluations.
4) The acquiring phase also adopts parameter adaption with a focus on directing the particles to explore around the leader rather than exploiting the same search space.
5) Linear population reduction technique (LPRT) to ensure heavy emphasis on exploration and diversification during the initial half of the search and transition to exploitation is implemented to enable a higher initial population. LPRT and distance-based strategy adaption ensure the prevention of early entrapment to make sure that the search process continues to adapt to complex landscapes.
6) Population elimination feedback from the population being discarded due to the reduction of population is considered to help guide the remaining population members to explore the potentially promising areas in the search space.

B. IMPLEMENTATION

ME-SGO is implemented in two phases similar to SGO, which are the enhanced improving phase with global search and adaptive acquiring phases respectively. In each phase, the greedy selection technique is implemented to select the newer population with better fitness than its predecessors. Linear population reduction strategy is applied on top of the whole exploration system to encourage deeper exploration and enable a smooth transition from exploration to exploitation. The individual phases are detailed as follows.

1) ENHANCED IMPROVING PHASE WITH GLOBAL SEARCH

The improving phase in SGO is aimed at exploring around the Leader to further improve the solution quality. The *self-introspection factor* set through empirical analysis servers as a control mechanism to limit the velocity of each population member. The greedy selection follows the improving phase to ensure that the fittest members are included while the others are discarded. Although it has been effective for most unimodal and a few multi-modal problems, this system is often prone to local entrapment as a result of excessive dependence on the leader in dynamic search landscapes especially resulting in poor performance for the shifted and rotated composite landscapes. Population stagnation can occur if the fitness of a member fails to improve since the greedy selection discards any solution with an inferior fitness.

The enhanced improving phase incorporates much more efficient strategies to explore a vast majority of the landscape while learning from the experience of the leader. This system incorporates the previous improving operator with a new modified improving operator and a modified differential mutation operator to allow for a larger exploration of the search space and prevent it from quickly transitioning to exploitation. The enhanced improving phase is split into two sub-phases with the first phase known as the enhanced explorative phase implemented for the first half of the function evaluations followed by the enhanced exploitative phase for the other half as described in (4).

$$\vec{P}_{new}(t+1) = \begin{cases} \textit{Enhanced Explorative phase} \\ \quad NFEs < 0.5 * Total\ NFEs \\ \textit{Enhanced Exploitative phase} \\ \quad otherwise \end{cases} \tag{4}$$

The enhanced explorative phase is designed to take advantage of the increased population available during the initial stages of the search process. Enhancement of diversity is set as the primary goal of this process and the newer solutions are generated through combinations of multiple difference vectors to drive the current population to explore the vastness of the search landscape. The equations concerning the generation of new a solution is described by (5) and (6) respectively.

Randomly select a member $\boldsymbol{P_r}$ *from the population pool such that* $\boldsymbol{i \neq r}$

If $f(\boldsymbol{P_i}) < f(\boldsymbol{P_r})$

$$\vec{P}_{i,j}^{(t+1)} = R \times \vec{P}_{i,j}^{(t)} + r_1 \times \left[\vec{X}_1\right] + r_2 \times \left[\vec{Y}_1\right] + r_3 \times \left[\vec{Z}_1\right] \tag{5}$$

where

$$\vec{X}_1 = \left[\vec{P}_{r,j}^{(t)} - \vec{P}_{i,j}^{(t)}\right]$$

$$\vec{Y}_1 = \left[Leader_j - \vec{P}_{r,j}^{(t)}\right]$$

$$\vec{Z}_1 = \left[\vec{P}_{r,j}^{(t)} - \vec{Worst}_t\right]$$

Else

$$\vec{P}_{i,j}^{(t+1)} = C_D \times \vec{P}_{r,j}^{(t)} - r_1 \times \left[\vec{X}_2\right] - r_2 \times \left[\vec{Y}_2\right] - 0.1 \times \left[\vec{Z}_2\right] \tag{6}$$

where

$$\vec{X}_2 = \left[Leader_j - \vec{P}_{i,j}^{(t)}\right]$$

$$\vec{Y}_2 = \left[Leader_j - \vec{P}_{r2,j}^{(t)}\right]$$

$$\vec{Z}_2 = \left[\vec{Worst}_t - \vec{P}_{i,j}^{(t)}\right]$$

end if

where,

$\vec{X}$, $\vec{Y}$ and $\vec{Z}$ denote the difference vectors designed to promote the population diversity, $\vec{P}_{i,j}^{(t)}$ is the position of the i^{th} population for the j^{th} dimension in the t^{th} iteration, $\vec{P}_{r,j}^{(t)}$ and $\vec{P}_{r2,j}^{(t)}$ denote the positions of any two randomly chosen population members from the current iteration, $\boldsymbol{Leader_j}$ is the best solution obtained so far and $\vec{\boldsymbol{Worst}}_t$ is the worst solution from the current iteration, $\boldsymbol{C_D}$ stands for the success-history based dynamic *self-introspection factor* in the range 0.1 and 1. $\boldsymbol{R}$ is a random number in 0 and 1 dynamically updated at the end of every iteration and for every reset of $\boldsymbol{C_D}$

The inclusion of the worst solution is to ensure that diversity is preserved during exploration. Multiple difference vectors prevent the clustering of solutions at a single point and the adaptive *self-introspection factor* allows for controlled freedom of the particle to navigate and expand the solution space.

The enhanced exploitative phase includes the original position update equation from SGO and adds a novel feedback position update system with a probabilistic selection between both strategies. This is described by (7) and (8) respectively

Obtain a random value for "Sel" through uniform distribution

If $\boldsymbol{Sel > 0.5}$

$$\vec{P}_{i,j}^{(t+1)} = C_R \times \vec{P}_{i,j}^{(t)} + r_1 \times \left[Leader_j = \vec{P}_{i,j}^{(t)}\right] \tag{7}$$

Else

$$\vec{P}_{i,j}^{(t+1)} = C_R \times \vec{P}_{i,j}^{(t)} + F \times \left[\vec{P}_{FB\text{-}Leader,j}^{(t)} - \vec{P}_{r2,j}^{(t)}\right] - 0.01 \times \left[\vec{P}_{r3,j}^{(t)} - \vec{P}_{FB\text{-}Worst,j}^{(t)}\right] \tag{8}$$

where

$$\vec{P}_{FB\text{-}Leader,j}^{(t)} = \begin{cases} FB\text{-}Leader, j & \textit{if Np is reduced} \\ \vec{P}_{r,j}^{(t)} & \textit{otherwise} \end{cases}$$

$$\vec{P}_{FB\text{-}Worst,j}^{(t)} = \begin{cases} FB\text{-}Worst, j & \textit{if N p is reduced} \\ \vec{P}_{r,j}^{(t)} & \textit{otherwise} \end{cases}$$

$$F = 1 + rand + C_R$$

end if

where,

Sel is the exploitation scheme selector, ***FB-Leader*** **and** ***FB-Worst*** denote the best and worst solutions from the eliminated population set to provide feedback to the current population, $\boldsymbol{C_R}$ is known as the randomized *self-introspection factor* re-initialized in the range 0.2 to 1.0 with respect to the *learning rate* and $\boldsymbol{F}$ denotes the scaling factor.

2) ADAPTIVE ACQUIRING PHASE

The acquiring phase in SGO is focused on enhancing population diversity through comparative learning between the population members and the leader. This phase is inspired by the information exchange in society as each population member interacts with other random members while also interacting with the leader. Information is either transferred or gained between the members of the population based on the intellect of the two members interacting. The acquiring phase contributes to a quicker convergence and the inclusion of a greedy operator for every new solution combination may lead to loss of population diversity.

The adaptive acquiring phase implements a fitness-based selection system between the two population members devised below to improve the diversity of the population being generated. Premature convergence as a result of entrapment and stagnation can be avoided through this method. Re-initialization has not been considered since its contribution to the overall population diversity is negligible with the current greedy selection technique. The population update equations are specified by (9) and (10) respectively.

Randomly select a member $\boldsymbol{P_r}$ *from the population pool such that* $\boldsymbol{i \neq r}$

If $f(\boldsymbol{P_i}) < f(\boldsymbol{P_r})$

$$\boldsymbol{P_{i,j}^{(\vec{t}+1)} = P_{i,j}^{(\vec{t})} + C_D \times \left[Leader_j - P_{r,j}^{(\vec{t})}\right]} \tag{9}$$

Else

$$\boldsymbol{P_{i,j}^{(\vec{t}+1)} = P_{i,j}^{(\vec{t})} - C_D \times \left[Leader_j - P_{r,j}^{(\vec{t})}\right]} \tag{10}$$

end if

C. LINEAR POPULATION REDUCTION TECHNIQUE (LPRT)

The population management in ME-SGO is done through a linear population reduction technique where the members in the population pool are gradually decreased from a maximum population size to a minimum population size, both of which can be set as required. The key advantage of this strategy is that the exploration quality is enhanced by a larger degree and the risk of local entrapment and premature convergence is minimized. Since, every population member is compared to their leader and its previous iteration counterpart, the information exchange is adequate such that the elimination of members in the population pool is unlikely to have any effect on the outcome of the exploration. Initially, as the algorithm beings the search, it can sample a large number of solution combinations and as the iterations progress, a smooth transition from exploration to exploitation is possible.

The population updating process occurs twice in every iteration allowing for more interactions between the member in the population pool and generating new population members with good diversification and superior fitness. The absence of any sorting procedure to further sort and select the next generation of population enables the proposed method to be quicker than the algorithms, thereby reducing its time complexity. The upper limit and lower limit for the population size can be set based on the number of function evaluations (NFEs) and it is recommended for adequate exploitation to occur, the lower limit of the population be at least one-tenth of the upper limit. The population size is determined as per (11).

$$\boldsymbol{N_P = round\left[\left(N_{P_{max}} - NFE_{current}\right) \times \frac{\left(N_{P_{max}} - N_{P_{min}}\right)}{Max\ NFEs}\right]} \tag{11}$$

D. PARAMETER ADAPTION

The key to improving the performance of SGO is to dynamically adapt the *self-introspection factor* to the complex landscapes through a series of successes and failures. Authors at [23] demonstrated this through an investigative analysis of the various inertial control schemes for various unimodal and multi-modal landscapes with the concussion that a static setting of 'c' $= 0.2$ is often the best for unimodal landscapes while inertia-based increments to 'c' with respect to the progression of iterations can be exploited for multi-modal landscapes. Grounding on this, a learning mechanism to increment the value of $\boldsymbol{C_D}$ is devised as per (12).

$$\boldsymbol{C_{D_{new}}} = \begin{cases} \boldsymbol{C_{D_{old}}} & \textit{Failures} < \textit{learning rate} \\ \left(\boldsymbol{0.2} \times \boldsymbol{C_{D_{int}}}\right) + (\boldsymbol{0.2} \times \boldsymbol{rand}) & \\ & \textit{Failures} \geq \textit{learning arte} \end{cases} \tag{12}$$

As per the adaptive scheme, the value of $\boldsymbol{C_D}$ retained for the successful new population with improved fitness and is re-initialized for the maximum number of failures. Failures are set to zero at the initialization and are incremented by 1 for every population member that fails to generate a superior offspring in either the enhanced improving phase or the adaptive acquiring phase. The *learning rate* is devised (empirically set to 10) to ensure that every new combination of $\boldsymbol{C_D}$ is given an ample number of trials to improve the quality of the solution. Besides $\boldsymbol{C_D}$,the values of $\boldsymbol{C_R}$ is set to be re-initialized within the range of 0.2 to 1.0 (the recommended range for c from the standard SGO) whenever $\boldsymbol{C_D}$ is modified and $\boldsymbol{R}$ being randomized in the range 0.1 to 1.0 at the end of every iteration and whenever $\boldsymbol{C_D}$ is modified to ensure that static settings for control parameters are avoided to the most possible extent.

E. EXPLORATION VERSUS EXPLOITATION

Besides the distance-based strategy adaption and success-based parameter adaption, the dynamic population control through LPRT serves as the backbone to efficiently balance exploration and exploitation. While the distance-based strategy adaption ensures that population diversity is enhanced, LPRT ensures that the maximum possible population is dedicated to it. The initial higher population enhances the reach of the population to multiple corners of the search space across multiple dimensions as it proceeds to exploit them during the latter stages. As the population size is lowered, the feedback enhanced exploitation phase from the enhanced improving phase proceeds to exploit the most promising areas discovered thereby improving the accuracy of the solutions. The adaptive acquiring phase extends the exploration to a global scale pushing the remaining population to further explore after the first explorative phase thus extending the

TABLE 3. Time complexity of ME-SGO.

Operation	Time	Total Time required for population sizer of N_p	Time Complexity
Initialization	t_1	$t_1 \times N$	$O(N_p)$
Fitness evaluation of the initialized population	t_2	$t_2 \times N$	$O(N_p)$
Enhanced Improving phase	t_3	$t_3 \times N$	$O(N_p)$
Fitness evaluation for the greedy selection	t_4	$t_4 \times N$	$O(N_p)$
Adaptive Acquiring phase	t_5	$t_5 \times N$	$O(N_p)$
Fitness evaluation for the greedy selection	t_6	$t_6 \times N$	$O(N_p)$

exploration over a larger timeframe and allowing the population to explore and exploit simultaneously. The ensemble of these strategies allows for explosive exploration while allowing smoother yet careful exploitation over the course of iterations to achieve a near-perfect balance of the exploration and exploitation dynamically.

F. TIME COMPLEXITY AND COMPUTATIONAL COMPLEXITY

The position update system in ME-SGO occurs twice i.e., the first position update in improving phase followed by the second position update in the acquiring phase. The greedy selection follows both the phases to decide on preserving the fitter solutions or discarding the inferior ones. The fitness evaluation and the position updates are performed for all the members in the population pool twice in an iteration. Hence, it is obvious that ME-SGO performs double fitness evaluations (DFEs) per iteration. For an iterative count of T iterations with a population size of N each having a D number of decision variables/dimensions, the following are the computational complexities of individual phases. The computational complexity of initialization is $O(D)$, the computational complexity of the fitness evaluation is $O(N)$, the computational complexity of the position updation is $O(T \times (N \times D))$. This is followed by fitness evaluation of all the new position for the greedy selection with $O(N \times T)$. Since, ME-SGO relies DFEs and updates the position of the population twice in every iteration, the total computational complexity of is $O(N \times (D + 2 \times (T + (T \times D))))$.

In the same manner, the time complexity of ME-SGO is measured considering its total run time i.e., 't_{total}' for one independent run. It is as shown in 13.

$$t_{total} = t_1 \times O_1 + t_2 \times O_2 + \ldots\ldots t_N \times O_N \tag{13}$$

where,

$t_1, t_2 \ldots\ldots t_N$ are the computational times needed by SGO to complete the various operations $O_1, O_2 \ldots\ldots O_N$ for N population size. The various operations and the time requirements are presented in Table 3.

Hence, from Table 3, it can be concluded that the time complexity of ME-SGO is $O(N)$.

IV. BENCHMARKING ANALYSIS

The benchmarking of the proposed method is performed in two phases i.e., the first phase comprises of benchmarking test functions following the latest standards (10 complex multi-modal functions from the CEC2019 test suite for the single-objective optimization) followed by the second phase with 5 constrained standard engineering problems (pressure vessel design, welded beam design, cantilever beam design, tension/compression spring design and 10-bar truss design optimization). All the experimentations considered for the current work are performed on a *hp* Ultrabook running the operating system of Microsoft Windows 10® Pro (Version 20H2 - OS Build 19042.1165) with 16 Gigabytes of DDR3 RAM powered by an Intel(R) Core (TM) i7-4700MQ quad-core CPU @ 2.40GHz. MATLAB R2020a is chosen to code all the algorithms for all the considered exterminations in the comparative analysis.

A. PERFORMANCE EVALUATION CRITERIA

The performance evaluation criteria are as follows. (1) The best, worst, average (mean) and standard deviation values are obtained based on 51 independent runs for all the all algorithms in comparison. (2) The first statical test, i.e., Wilcoxon's rank-sum test at a 0.05 significance level is performed for ME-SGO concerning the other algorithms. For better performance of the other algorithms with respect to ME-SGO "+" symbol is used, for the similar performance of the other algorithms with respect to ME-SGO "≈" symbol is used and for the inferior performance of the other algorithms concerning ME-SGO "-" symbol is used. (3) The second statistical test, i.e., a ranking test through a non-parametric Friedman's test is performed to rank the best-performing algorithms. (4) Furthermore, the mean absolute errors (MAE) to indicate the difference between the global optimal solution and the best solution obtained by each algorithm is evaluated. (5) The convergence graphs are provided for the CEC2019 benchmarking suite to showcase the converge characteristics of the proposed method. (6) The population diversity plots (Analysis of variance – ANOVA/box plots) are provided for the CEC2019 benchmarking suite. (7) The average computational times (Seconds) for the 51 runs are recorded.

The flowchart of ME-SGO is presented in Figure 2 (**Appendix**).

B. ALGORITHMS IN THE BENCHMARKING FRAMEWORK

1) The performance of ME-SGO is compared and validated against the standard SGO algorithm from 2016 and four of its latest state-of-the-art variants whose description is provided in Table 4.
2) Additionally, five state-of-the-art advanced meta-heuristics namely, EPSO, MPEDE (with Linear Population Reduction) being the multi-strategy

Algorithm 1 Pseudo-Code of ME-SGO

Start
Initialize *NP, T, C, rate, dim,* L_b, U_b
Set *c to 0.2, rate to 10, Failures to 0;*
The initial population is generated randomly with a size of 'NP×dim'
Identify *the leader/gbest and the worst*
  for $t = 1$ *to T*
    for $i = 1$ *to Np*
    *Implement "**Enhanced Improving phase**"*
$$\vec{P}_{new}(t+1) = \begin{cases} \textit{Enhanced Explorative phase} & NFEs < 0.5 * Total\ NFEs \\ \textit{Enhanced Exploitative phase} & otherwise \end{cases}$$
    end *Enhanced **Improving phase***
    *Implement "**Greedy Selection I**"*
    Update $\boldsymbol{C_D}$
$$C_{D_{new}} = \begin{cases} C_{D_{old}} & Failures < learning\ rate \\ (\mathbf{0.2} \times C_{D_{int}}) + (0.2 \times \boldsymbol{rand}) & Failures \geq learning\ rate \end{cases}$$
Update *the leader/gbest and the worst*
    *Implement "Adaptive **Acquiring phase**"*
    Set $i \neq r$
    If $f(P_i) < f(P_r)$
$$\vec{P}_{i,j}^{(t+1)} = \vec{P}_{i,j}^{(t)} + C_D \times \left[Leader_j - \vec{P}_{r,j}^{(t)} \right]$$
    else
$$\vec{P}_{i,j}^{(t+1)} = \vec{P}_{i,j}^{(t)} - C_D \times \left[Leader_j - \vec{P}_{r,j}^{(t)} \right]$$
    end Adaptive Acquiring phase
    *Implement "**Greedy Selection II**"*
    Update $\boldsymbol{C_D}$
$$C_{D_{new}} = \begin{cases} C_{D_{old}} & Failures < learning\ rate \\ (\mathbf{0.2} \times C_{D_{int}}) + (\mathbf{0.2} \times \boldsymbol{rand}) & Failures \geq learning\ rate \end{cases}$$
Update *the leader/gbest and the worst*
    end *for-Np*
  end *for-T*
Update *Np*
$$N_P = round\left[\left(N_{P_{max}} - NFE_{current}\right) \times \frac{\left(N_{P_{max}} - N_{P_{min}}\right)}{Max\ NFEs} \right]$$
Check the termination criteria
Stop

ensemble variants, CLPSO, GABC, and L-SHADE being the learning and adaptive have been employed to assess the performance of the proposed method. A brief description of the five state-of-the-art advanced meta-heuristics is provided in Table 4 and their categorization in Table 5.

3) In addition to the aforementioned variants of SGO, four of the modern meta-heuristics (GWO, WOA, SMA and ChOA) and one recent multi-strategy ensemble variant (MEGWO) are selected for the testing and validation process. A brief description of the four modern meta-heuristic and the multi-strategy ensemble variant is provided in Table 4.
4) To assess the performance of the proposed methods with the top performers for each benchmarking suite, the results winners/top-performing algorithms are also added in their sub-sections to provide a comprehensive analysis of the current standings of the proposed method.

C. TUNING SETTINGS OF THE ALGORITHMS

To ensure that a fair comparison is achieved, it required to set/tune the algorithm-specific parameters (tuning parameters) appropriately to extract the best performance. Hence, after a meticulous review of the various algorithms' performances, the following tuning settings have been finalized to ensure that the chosen algorithms deliver their best performance to the fullest of their potential. Please note that the values of the tuning parameters provided in Table 30 (**Appendix**) remain the same for the entire benchmarking

TABLE 4. Description of the state-of-the-art meta-heuristics used in the comparative analysis.

Categorization	Name of the variant	Authors	Year	Reference
Latest advanced variants of SGO	**HS-WOA+** (Extended variant of hybrid social whale optimization algorithm)	K.V.L. Narayana et al.	2020	[35]
	HS-WOA (Lite version of hybrid social whale optimization algorithm)	K.V.L. Narayana et al.	2020	[35]
	MSGO (Modified Social Group Optimization)	A. Naik et al.	2020	[30]
	ISGO (Improved Social Group Optimization)	J. Fang et al. in	2019	[27]
Modern meta-heuristics	**GWO** (Grey Wolf Optimizer)	S. Mirjalilin et al.	2014	[36]
	WOA (Whale Optimization Algorithm)	S. Mirjalili, A. Lewis	2016	[37]
	SMA (Slime Mould Optimization Algorithm)	S. Li et al.	2020	[38]
	ChOA (Chimp Optimization Algorithm)	M.Khishe and M.R.Mosavi	2020	[39]
	MEGWO (Multi-strategy ensemble Grey Wolf Optimizer)	Q. Tu et al.	2019	[21]
State-of-the-art advanced meta-heuristics	**CLPSO (**Comprehensive Learning Particle Swarm Optimizer)	Liang et al.	2006	[40]
	MPEDE (Multi-population ensemble Differential evolution)	G. Wu et al.	2016	[15]
	GABC (*gbest* guided Artificial bee colony**)**	G. Zhu et al.	2010	[41]
	L-SHADE (Success history-based adaptive differential evolution with linear population reduction)	R. Tanabe et al.	2014	[42]

TABLE 5. Categorization of the state-of-the-art meta-heuristics used in the comparative analysis.

Algorithms	Adaptive Control Parameters	Linear Population Reduction	Multi-population ensemble	Multi-strategy ensemble
L-SHADE	✓	✓		
MPEDE	✓	✓	✓	
CLPSO	✓		✓	✓
EPSO	✓		✓	✓
GABC	✓			
MEGWO	✓			✓

process and real-world problems tackled in the remainder of the manuscript.

D. PERFORMANCE ANALYSIS WITH CEC2019 BENCHMARK FUNCTIONS

The 100-Digit Challenge from Special Session and Competition on Single Objective Numerical Optimization in 2019 introduced 10 special functions to be minimized with limited control parameter ''*tuning*'' for each function [43]. The test functions were meticulously crafted with multiple local optima and one unique global optimal solution to ensure that the exploratory prowess and local minima avoidance characteristics are put to test. Similar to composition functions from the previous CEC sessions, the CEC2019 benchmark suite presents challenging exploratory conditions with their landscape shifted and rotated to further complicate the search process of an algorithm. It is to be noted that these functions are extremely challenging for any global optimization algorithm to determine the global optimal solution as their formulation is such that they are intended to trap the algorithms at local best positions, especially for algorithms designed with a tendency to converge to the central point of the search landscape. Additionally, these problems have a large number of dimensions making the search process even harder and complex and only the algorithms with a higher exploratory tendency of the entire search space can determine the global optimal solution or generate solutions in close proximity to the global best.

The description of the CEC2019 benchmarking suite is shown in Table 31 (**Appendix**).

1) ANALYSIS OF BENCHMARKING PERFORMANCE WITH CEC2019 TEST FUNCTIONS

The CEC2019 benchmark suite provides a more graduated way to measure ''*horizontal*'' performance (accuracy) because even ''*failures*'' can have some correct digits. The complex test functions require a deeper exploration of the various corners and dark spots of the search landscape such that the algorithm can reach the global optimal solution and has been proven to be quite challenging for many state-of-the-art meta-heuristics. Considering that computational time has become less of an issue lately, the test suite does not impose restrictions on the number of function evaluations indicating that faster convergence is not the priority with the competitors.

To ensure a fair comparison, 50 independent runs have been considered for all the algorithms with 500,000 function evaluations (NFEs). All the algorithms have been given 1000 iterations with the population size set based on the requirements. The variants of SGO were given a population size of 250 as they relied on DFEs and the modern meta-heuristics were given 500 as they relied on (Single Function Evaluations per iteration (SFEs). L-SHADE, MPEDE were given an initial population size of 100 and a final population size of 4 with NFEs being the termination criteria. ME-SGO was given an initial population of 500 and a final population of 50 with NFEs being the termination criteria.

The benchmarking results (best, worst, mean and standard deviation) are shown in Table 6, the results of Wilcoxon's

TABLE 6. The values of best, worst, mean and the standard deviation of the sixteen algorithms for the CEC2019 benchmark functions.

		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
F1	Best	**1 (P)**	**1 (P)**	**1 (P)**	**1 (P)**	**1 (P)**	**1 (P)**	4.6410	**1 (P)**	**1 (P)**	1.8165	**1 (P)**	2.6433	**1 (P)**	**1 (P)**	**1 (P)**	**1 (P)**
	Worst	**1 (P)**	**1 (P)**	**1 (P)**	2949.5	**1 (P)**	405.61	6367.2	**1 (P)**	421.70	66.165	**1 (P)**	86.621	73.539	1 (P)	1.0000	**1 (P)**
	Mean	**1 (P)**	**1 (P)**	**1 (P)**	291.98	**1 (P)**	37.786	1438.7	**1 (P)**	100.93	25.156	**1 (P)**	30.055	10.587	1 (P)	1	**1 (P)**
	Std	**0**	**0**	**0**	744.26	**0**	82.919	1888.7	**0**	129.83	20.457	**0**	25.040	22.518	0	1.1E-07	**0**
F2	Best	4.1863	4.4064	4.2721	4.9630	4.2355	14.6523	4156.2	4.2390	32.507	8.1564	**1 (P)**	625.20	89.953	**1 (P)**	45.857	**1 (P)**
	Worst	4.6394	5	5	5	5	456.83	13587	5.0000	1723.4	12.151	**1 (P)**	2515.0	436.47	**1 (P)**	210.31	**1 (P)**
	Mean	4.3639	4.9488	4.8984	4.9988	4.7729	233.37	7903.5	4.3275	967.82	10.165	**1 (P)**	1688.0	228.39	**1 (P)**	122.53	**1 (P)**
	Std	0.1124	0.1309	0.2032	0.0067	0.3294	114.11	2689.8	0.1414	551.10	1.9418	**0**	464.47	86.526	**0**	37.039	**0**
F3	Best	1.0007	3.9995	1.0239	1.4103	1.0041	1.0057	1.4091	2.0092	2.7543	10.894	1.0000	1.0213	1.0000	4.1145	1.0001	**1 (P)**
	Worst	2.3289	7.5367	2.5212	4.9076	3.0155	4.6086	7.6330	7.7121	5.4243	12.329	1.0001	2.0906	1.4091	4.1467	2.9247	**1.5001**
	Mean	1.4907	6.0394	1.6347	2.0210	1.6979	1.6418	2.2107	3.5749	3.7461	11.458	1.0000	1.4119	1.3827	4.1321	1.4815	**1.2164**
	Std	0.3519	0.8105	0.4220	0.8556	0.4340	0.8323	1.4329	2.0847	0.6854	0.3297	2.1E-05	0.1810	0.1022	8.5E-14	0.5377	**0.1884**
F4	Best	6.9698	61.320	6.9697	18.081	9.3901	3.0103	15.924	2.9900	31.873	3.9988	1.8214	1.9950	2.9899	**1.0015**	1.9967	1 .8451
	Worst	54.728	112.72	39.803	75.351	44.944	28.807	71.642	14.781	54.660	6.7154	4.9214	5.1949	13.934	**4.7895**	12.034	5.9798
	Mean	29.437	83.227	22.631	43.278	25.546	9.0756	38.270	8.8450	40.730	5.6487	3.2815	3.7394	7.2586	**2.3154**	6.5270	3.1889
	Std	11.332	11.565	7.9888	12.428	8.3048	5.7112	15.905	3.2322	5.1627	0.9461	0.2354	0.9367	2.1828	1.0284	2.9319	1.0276
F5	Best	1.1674	42.375	1.0787	1.8801	1.5737	1.0698	1.1760	1.1157	2.2194	1.0101	**1 (P)**	1.0000	1.0246	**1 (P)**	1.0285	**1 (P)**
	Worst	2.2011	102.61	1.4973	5.5299	2.0806	1.7814	2.7281	1.3944	33.407	1.0548	1.0258	1.0254	1.3812	1.0894	1.1244	**1.0041**
	Mean	1.4298	57.910	1.2318	3.2820	1.8830	1.3217	1.7279	1.1994	9.6612	1.0301	1.0111	1.0063	1.1058	1.0286	1.0720	**1.0022**
	Std	0.2492	13.361	0.1143	1.0026	0.1295	0.1948	0.3983	0.0805	6.8115	0.0204	0.0214	0.0065	0.0769	0.0412	0.0274	0.0024
F6	Best	1.9885	8.6207	2.2889	4.9558	1.8276	1.1340	3.7198	1.5642	5.3780	1.4156	**1 (P)**	1.0018	1.0002	**1 (P)**	1.0906	**1 (P)**
	Worst	8.9731	12.086	7.5515	11.793	7.5137	3.5852	9.4972	5.0853	8.1599	1.9515	**1 (P)**	1.5475	2.8166	1.8515	4.9928	**1 (P)**
	Mean	4.9984	10.584	5.1331	7.7156	4.3334	1.5689	7.0091	2.8365	6.1565	1.5977	**1 (P)**	1.1101	1.3660	1.2644	2.5067	**1 (P)**
	Std	1.4585	0.8084	1.4759	1.5587	1.2289	0.5756	1.4788	1.2880	1.6568	0.0483	**0**	0.1803	0.5606	0.3648	1.4714	**0**
F7	Best	348.27	1360.8	347.76	612.53	24.447	45.636	665.30	97.996	796.86	121.65	**1.1215**	1.2528	1.1249	5.1547	347.76	1.5489
	Worst	1484.8	2402.7	1362.3	1642.5	1505.2	1096.8	1772.4	776.09	1663.9	294.72	**72.154**	149.45	664.58	299.15	1362.31	338.13
	Mean	976.14	1947.8	822.73	1132.8	818.37	408.67	1125.7	404.21	1297.1	134.84	**20.548**	58.472	323.22	95.015	822.73	90.092
	Std	290.44	214.67	293.76	294.82	352.75	210.90	277.03	188.03	198.69	46.304	**19.189**	58.447	183.44	98.156	293.76	70.848
F8	Best	3.1993	4.4000	3.0644	3.5675	3.0542	1.2090	3.1987	1.8306	3.7774	2.8871	1.5617	1.5193	**1.2891**	1.8451	2.2601	1.4587
	Worst	4.5029	5.2453	4.5099	4.9764	4.7043	3.5681	4.6377	3.9690	4.9023	3.4315	2.8465	3.1349	**3.1134**	2.9478	4.1534	2.9651
	Mean	3.7858	4.9911	3.8258	4.3711	3.8749	2.7095	4.0439	3.1105	4.4666	2.9154	2.2648	2.3311	**2.1444**	2.5484	3.2216	2.3531
	Std	0.3879	0.1940	0.3542	0.2955	0.3924	0.6454	0.3396	0.4771	0.2536	0.2326	0.3216	0.3749	0.5159	0.3151	0.5712	0.5612
F9	Best	1.0556	2.5623	1.0911	1.2073	1.1670	1.0248	1.0927	1.0483	1.1297	1.1154	1.0354	1.0457	1.0562	1.0548	1.0505	**1.0105**
	Worst	1.4056	3.9220	1.3242	1.8676	1.6759	1.1220	1.7289	1.2469	1.4870	1.2139	1.0404	1.1593	1.1661	1.4841	1.1266	**1.1248**
	Mean	1.2056	3.2522	1.1947	1.4294	1.3083	1.0795	1.3705	1.1192	1.3321	1.1845	1.0394	1.0998	1.0957	1.2676	1.0835	**1.0927**
	Std	0.0959	0.3788	0.0651	0.1537	0.1012	0.0237	0.1702	0.0455	0.0967	0.0264	0.0154	0.0237	0.0254	0.1463	0.0190	**0.0215**
F10	Best	1.0076	21.076	2.1551	12.069	2.9850	2.0133	21.000	1.5175	21.155	8.5514	1.0001	1.0042	**1 (P)**	**1 (P)**	21.146	**1 (P)**
	Worst	21.307	21.407	21.322	21.336	21.413	21.370	21.335	21.029	21.412	21.048	21.024	21.036	**21.255**	**21.004**	21.345	**21.189**
	Mean	14.861	21.287	18.921	20.648	19.602	20.628	21.037	19.074	21.301	13.651	10.066	12.964	**5.680**	**9.2145**	21.251	**8.102**
	Std	7.7375	0.0827	6.0256	2.2666	5.2020	3.4552	0.0816	6.0076	0.0608	4.1052	9.8009	9.2651	**8.5340**	**9.1254**	0.0421	**7.5719**

(P) indicates that the precision of the algorithm was accurate up to the ten decimal places

TABLE 7. The *p*-values obtained from the Wilcoxon's rank sum test comparing ME-SGO with the fifteen algorithms for the CEC2019 benchmark functions.

	SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO
F1	3.82E-03 (-)	6.85E-03 (-)	3.51E-04 (-)	6.65E-09 (-)	1.06E-03 (-)	1.49E-09 (-)	7.53E-09 (-)	8.17E-02 (≈)	4.90E-09 (-)	4.98E-08 (-)	9.50E-02 (≈)	3.53E-07 (-)	2.90E-08 (-)	1.37E-02 (≈)	6.00E-03 (-)
F2	9.48E-06 (-)	2.15E-07 (-)	1.05E-06 (-)	5.16E-06 (-)	2.83E-05 (-)	4.23E-09 (-)	7.38E-09 (-)	6.91E-04 (-)	4.47E-09 (-)	9.51E-09 (-)	5.46E-02 (≈)	2.03E-09 (-)	7.52E-09 (-)	5.67E-02 (≈)	2.68E-09 (-)
F3	5.18E-04 (-)	6.89E-06 (-)	8.94E-03 (-)	6.05E-04 (-)	5.46E-03 (-)	9.07E-03 (-)	3.94E-04 (-)	3.21E-04 (-)	6.43E-05 (-)	3.44E-05 (-)	1.46E-01 (+)	2.56E-03 (-)	7.49E-03 (-)	4.70E-04 (-)	6.51E-03 (-)
F4	5.17E-09 (-)	5.14E-09 (-)	6.17E-06 (-)	8.36E-07 (-)	9.48E-05 (-)	7.86E-05 (-)	6.52E-07 (-)	9.41E-04 (-)	7.05E-06 (-)	5.84E-04 (-)	1.56E-03 (-)	6.14E-03 (-)	3.83E-04 (-)	2.17E-02 (≈)	6.85E-04 (-)
F5	6.85E-03 (-)	5.87E-08 (-)	7.15E-03 (-)	1.86E-05 (-)	9.56E-04 (-)	9.50E-03 (-)	1.78E-04 (-)	4.38E-04 (-)	7.50E-07 (-)	2.29E-03 (-)	2.62E-02 (≈)	4.74E-02 (≈)	5.66E-03 (-)	3.40E-02 (≈)	7.43E-03 (-)
F6	7.61E-05 (-)	7.71E-05 (-)	9.16E-05 (-)	6.89E-07 (-)	1.64E-06 (-)	6.53E-03 (-)	7.02E-07 (-)	4.40E-04 (-)	2.81E-06 (-)	7.46E-03 (-)	8.34E-03 (-)	3.55E-03 (-)	1.84E-03 (-)	1.69E-03 (-)	4.52E-04 (-)
F7	6.89E-07 (-)	2.16E-08 (-)	4.89E-08 (-)	8.14E-08 (-)	9.61E-08 (-)	4.50E-08 (-)	4.41E-08 (-)	3.84E-06 (-)	6.76E-08 (-)	2.60E-03 (-)	2.59E-01 (+)	8.24E-02 (≈)	5.63E-05 (-)	7.88E-03 (-)	4.92E-07 (-)
F8	8.41E-04 (-)	8.65E-05 (-)	7.42E-05 (-)	5.47E-04 (-)	9.48E-04 (-)	8.42E-03 (-)	2.81E-05 (-)	7.60E-05 (-)	6.52E-04 (-)	5.06E-04 (-)	8.08E-02 (≈)	5.84E-02 (≈)	5.30E-02 (≈)	3.15E-03 (-)	2.34E-05 (-)
F9	8.43E-04 (-)	4.98E-06 (-)	2.15E-03 (-)	9.16E-04 (-)	4.86E-03 (-)	9.25E-02 (≈)	4.55E-04 (-)	7.89E-03 (-)	1.69E-04 (-)	6.95E-03 (-)	2.49E-02 (≈)	5.49E-03 (-)	7.74E-02 (≈)	5.28E-04 (-)	9.05E-02 (≈)
F10	3.32E-03 (-)	3.18E-07 (-)	3.56E-04 (-)	7.96E-08 (-)	7.94E-08 (-)	6.75E-08 (-)	1.05E-08 (-)	1.93E-08 (-)	1.27E-09 (-)	8.83E-03 (-)	9.21E-03 (-)	9.09E-03 (-)	9.25E-01 (+)	1.72E-03 (-)	1.59E-09 (-)
L (-)	10	10	10	10	10	9	10	9	10	10	3	7	7	6	9
W (+)	-	-	-	-	-	-	-	-	-	-	2	-	1	-	0
T (≈)	-	-	-	-	-	1	-	1	-	-	5	3	2	4	1

rank-sum test are shown in Table 7, the mean absolute error (MAE) for all the fifteen algorithms and the results of Friedman's non-parametrical test are shown in Table 8 and the average computational times (ms) are shown in Table 9 respectively.

2) THE 100-DIGIT COMPETITION

The scoring system considers the average number of correct digits in the best 25 out of 50 trials such that an accurate representation of the performance of the algorithm is provided. Furthermore, compared to the latest CEC2020 benchmarking suite, where the test functions from previous sessions were re-used, the CEC2019 session provides tailor-made, meticulosity designed test functions which also provides a measure of the accuracy and precision of the search technique being used. The CEC2019 suite allows for a limited control parameter "*tuning*" for each function which can double as a method to validate the tuning sensitivity of the proposed method and compare it with the winners of the competition. A maximum of 1E+08 NFEs was allowed for all the functions as the termination criteria and the performance of ME-SGO is shown in Table 10. Comparison of ME-SGO's score (rounded-off) with the other top performing algorithms is shown in Table 11.

TABLE 8. Ranking the sixteen algorithms based on the Friedman's for the CEC2019 benchmark functions.

Algorithms	Friedman's rank	Mean Absolute Error	Generalized rank
L-SHADE	1.5214	3.22108	1
ME-SGO	2.0051	10.00473	2
MPEDE	2.1654	10.8786	3
CLPSO	3.0564	19.76464	4
SMA	4.5161	43.9297	5
EPSO	5.6641	57.22302	6
GWO	7.6516	70.7851	7
HS-WOA+	8.1564	87.23884	8
ISGO	8.2544	87.32005	9
MEGWO	9.5542	97.34033	10
SGO	10.8496	102.87122	11
HS-WOA	12.5645	150.25239	12
GABC	14.6546	179.01896	13
MSGO	16.8451	213.10395	14
ChOA	18.1646	244.32435	15
WOA	25.35486	1053.3569	16

TABLE 9. Comparison of the computational times (ms) of the eleven algorithms for the CEC2019 benchmark functions.

	SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
F1	13.0713	9.7474	13.8433	14.8295	12.5953	5.0317	4.3000	12.8923	24.5937	23.1160	7.5169	13.7051	25.8141	8.8607	10.4089	8.1776
F2	8.6120	7.3593	9.3219	10.0389	8.2539	4.0535	2.4747	12.8382	34.9985	19.5770	7.9652	8.1065	24.1784	9.2785	5.7166	7.0378
F3	8.4724	7.8851	9.4037	9.8853	8.5096	4.2017	2.6047	12.8231	36.1548	19.7141	8.0217	8.6846	33.6156	9.1565	5.5204	7.0122
F4	9.2995	6.7640	9.4687	10.1485	8.4143	3.6086	2.7028	11.2407	23.3079	17.9957	9.1426	8.5149	22.4310	10.1821	5.5558	8.6165
F5	11.4689	8.7443	12.1167	13.0899	11.1287	3.6670	2.5564	12.3220	22.5155	23.7576	8.5620	10.8613	22.4347	9.3798	7.2833	12.5198
F6	34.1153	32.2517	34.4764	34.3399	32.9569	22.1361	21.3398	29.9730	261.1867	37.7809	10.6521	32.4362	42.6472	9.3798	31.4651	40.1562
F7	11.7799	8.6598	12.2957	13.0869	10.7614	3.7326	2.7663	11.2741	22.7771	23.3775	8.9199	11.6768	29.3584	11.1264	12.2957	12.6815
F8	10.9958	8.4853	11.8317	12.5310	10.6620	3.6538	2.5561	11.2974	22.4358	23.1219	10.5450	10.3538	28.6163	12.1512	7.2306	10.1562
F9	10.6770	8.0794	11.4782	12.1496	10.2894	3.4609	2.4086	10.9697	22.7950	22.0983	8.1968	9.8311	28.9415	9.9084	6.5874	12.1562
F10	10.2738	7.9312	10.7422	11.8173	9.9596	3.5999	2.6422	11.3211	22.7919	21.6100	7.9875	9.4945	30.9275	8.2051	6.6602	12.8950

TABLE 10. Final scores of ME-SGO for the 100-digits challenge.

Function	0	1	2	3	4	5	6	7	8	9	10	Score	Max NFEs
F1											50	10	2.9E+04
F2											50	10	3.8E+06
F3				22							28	10	9.8E+06
F4	28	21	1	1							2	1	1E+08
F5		22									28	10	7.1E+05
F6											50	10	9.1E+06
F7	27	19	2	1							2	1	1E+08
F8		1	43	6								3	1E+08
F9			42	8								3	1E+08
F10	20										30	10	4.3E+05
Score												68	

TABLE 11. Comparison of the scores of the top-performing algorithms for the CEC2019 100-digit challenge.

Algorithm	Score	Rank
jDE100 [44]	100	1
HyDE-DF [45]	93	2
CIPDE [46]	85	3
DISH [47]	83.92	4
GADE [48]	71.96	5
ME-SGO	68	6
DLABC [49]	67.88	7
MiLSHADE-LSP [50]	60.72	8
ESP-SOMA [51]	51.92	9

Analysis of Results:

1) The performance of ME-SGO has been excellent for F1, F2, F3, F5, F6 and F10. The proposed method achieved the 10-digit accuracy for these functions with minor deviations in terms of accuracy. The performance for functions F1, F2 and F6 have the best and both ME-SGO and L-SHADE have produced similar results.
2) Function F7 had been the most challenging for ME-SGO and could only outperform MPEDE while L-SHADE had been the best performing algorithm. The function F10 had similar outcomes from

TABLE 12. Tabulation of best, worst, average (mean), standard deviation and the average computational times (seconds) for the pressure vessel design from the 30 independent runs for the sixteen algorithms.

Algorithms	Best	Worst	Mean	Standard Deviation	Average Computational Time
ME-SGO	5885.3312509799	5979.7596103693	5891.1181201905	22.4313341327	0.2771
L-SHADE	5885.3315367749	5976.5297327623	5892.9100540970	22.0236908441	0.3584
MPEDE	5885.6218583630	6009.3105421747	5935.9703272727	49.2198996947	0.3381
EPSO	5885.3312508567	7318.9989210709	6125.0087354593	384.0367642831	0.7378
CLPSO	6110.5829295447	6202.0838536094	6157.7140609976	35.2511879165	0.1372
GABC	6061.6997485320	6265.8527398385	6165.3576777197	96.8523879118	0.1015
MEGWO	5908.1870610321	6434.8089904437	6171.0250813655	221.8932295329	0.0851
ISGO	5885.9827864557	7318.9937225151	6226.9112765049	423.1925176938	0.0790
GWO	5895.5021011051	7271.1849180084	6263.7459189117	513.5139797835	0.0682
SGO	5886.8003560724	7318.9989210708	6285.2499074233	369.9712646763	0.0800
SMA	5885.3917725061	7319.0052742464	6446.8437991134	529.6207730838	0.2542
HSWOA+	5935.9986303480	7880.5667454425	6683.7500352068	649.3751253418	0.0777
HSWOA	5994.6720636824	7474.0524772128	6782.1884083616	465.5344139496	0.0852
ChOA	7684.2457795734	9785.7984249093	8208.2348559745	552.3979536913	0.2192
WOA	7483.3366637680	113853.66120769	19957.38044634	26472.61283668	0.0650
MSGO	25951.381319747	549520.46604697	288534.8035376	108194.2142375	0.0620

L-SHADE, MPEDE and ME-SGO and for F8 and F9 all three of them performed similarly with ME-SGO being the best performer for F9.

3) It is quite evident that ME-SGO, L-SHADE and MPEDE have been the top-performing algorithms and the point of similarity is the integration of linear population reduction in all three of them. While it is clear that linear population reduction helps achieve a better exploration, it has been crucial to avoiding early entrapment as witnessed with the other algorithms.
4) ME-SGO's score of 68 in the 100-digit competition has been compared to other top performing algorisms. It ranked sixth overall outperforming other DE based optimizers. It is worth mentioning that only the initial population size and number of iterations have been modified to achieve this outcome as rules of the competition dictate. The adaptive parameters have not been modified, although it is possible that tuning the *learning rate* can help improve the performance for other such complex landscapes.

The convergence graphs for all the algorithms for the CEC2019 benchmarking suite are shown in Figure 3 (**Appendix**) and the ANOVA plots are shown in Figure 4 (**Appendix**)

E. PERFORMANCE ANALYSIS WITH STANDARD CONSTRAINED ENGINEERING PROBLEMS

In addition to the benchmarking tests, it is required to validate the performance of the proposed method with constrained engineering problems. Generally referred to as "*the standard engineering problems*", these design optimization problems have multiple constraints and requires the generation of a feasible optimal solution with no constraint violation. Hence, five standard engineering problems (requiring the objective function to be minimized) are chosen which include the SE1: pressure vessel design, SE2: welded beam design problem, SE3: cantilever beam design, SE4: tension/compression spring design problem and the SE5: 10-bar truss design optimization. The previous sixteen algorithms are included in the comparative analysis with no change to the tuning settings of the algorithm-specific parameters. All the algorithms considered for the comparative analysis are given 30 independent runs to determine the mean and standard deviation with the NFEs set to 10,000. Additionally, the best fitness score and its corresponding optimal decision variables, worst fitness score, the average computational times are recorded for all eleven algorithms.

The penalty function approach (static penalty function) is opted to handle the various constraints wherein a penalizing score (very high pre-set value) known as a penalty is added to the objective function for any violation of the constraints by the members of the population pool.

1) PRESSURE VESSEL DESIGN

A detailed description of the objective function, constraint functions and the range of the decision variables (mathematical formulation) for the pressure vessel design is shown in Table 32 (**Appendix**). The best fitness values and their corresponding optimal decision variables for all the sixteen algorithms sorted in the ascending order of their fitness scores are given in Table 33 (**Appendix**). A comparative tabulation of the best, worst, average, standard deviation and the average computational times of the 30 independent runs for all the fifteen algorithms is shown in Table 12.

2) WELDED BEAM DESIGN

A detailed description of the objective function, constraint functions and the range of the decision variables (mathematical formulation) for the welded beam design is shown in Table 34 (**Appendix**). The best fitness values and their corresponding optimal decision variables for all the sixteen algorithms sorted in the ascending order of their fitness scores are given in Table 35 (**Appendix**). A comparative tabulation of the best, worst, average, standard deviation and the average

TABLE 13. Tabulation of best, worst, average (mean), standard deviation and the average computational times (seconds) for the welded beam design from the 30 independent runs for the sixteen algorithms.

Algorithms	Best	Worst	Mean	Standard Deviation	Average Computational Time
MPEDE	1.7248523092	1.7248528760	1.7248523482	1.07E-07	0.4146
L-SHADE	1.7248523431	1.7250235326	1.7248617482	3.09E-05	0.3121
ISGO	1.7248523086	1.7347499178	1.7253138420	1.81E-03	0.0814
ME-SGO	1.7248718352	1.7272495493	1.7253946595	6.11E-04	0.2131
MEGWO	1.7248523086	1.7604474298	1.7272907337	9.18E-03	0.0819
SGO	1.7248523086	1.8499212711	1.7290978664	2.24E-02	0.0849
GWO	1.7265131462	1.7431677086	1.7316114946	4.66E-03	0.0703
EPSO	1.7248523243	1.8142933846	1.7420084978	3.36E-02	0.7295
SMA	1.7251226806	2.3589833566	1.7883982022	1.57E-01	0.2137
ChOA	1.8409799601	1.8849777067	1.8645590979	1.21E-02	0.2278
GABC	1.7427050667	2.0958825501	1.8799263146	1.02E-01	0.0917
HSWOA	1.7384337268	2.6979568854	1.9609319687	2.48E-01	0.0892
CLPSO	1.7395032302	2.4327943216	2.0114140654	2.19E-01	0.1251
HSWOA+	1.7375924903	5.6918747514	2.0782237057	7.70E-01	0.0788
WOA	1.9875489291	4.8829627452	2.9316213300	9.12E-01	0.0662
MSGO	2.9296353313	8.6376869845	5.3057368166	1.33E+00	0.0643

TABLE 14. Tabulation of best, worst, average (mean), standard deviation and the average computational times (seconds) for the cantilever beam design from the 30 independent runs for the sixteen algorithms.

Algorithms	Best	Worst	Mean	Standard Deviation	Average Computational Time
ME-SGO	1.33995636163	1.33995962476	1.33995701599	0.00000087392	0.1285
L-SHADE	1.33995675163	1.34012668650	1.33997545058	0.00003575208	0.4127
EPSO	1.33996725179	1.34015033980	1.34002275682	0.00005337529	0.6470
ISGO	1.33996051482	1.34042947532	1.34002491404	0.00011886728	0.0550
SGO	1.33996944407	1.34159345358	1.34004123767	0.00028954848	0.0578
MPEDE	1.33996566939	1.34034267357	1.34014552804	0.00013922643	0.4526
MEGWO	1.33999185203	1.34055722840	1.34014651353	0.00017949390	0.1050
GWO	1.33997812110	1.34058241259	1.34024273243	0.00016491679	0.0516
CLPSO	1.34013852742	1.34469531133	1.34152665585	0.00100518376	0.0975
HSWOA	1.34044457161	1.34808895815	1.34260204905	0.00170490167	0.0639
HSWOA+	1.34133868334	1.36515180438	1.35063164183	0.00600099114	0.0555
GABC	1.34853399859	1.38319808573	1.36194484193	0.01058366457	0.0609
ChOA	1.34936655039	1.39600463795	1.36909453552	0.01313582174	0.2494
SMA	1.56465826214	1.85858333032	1.67832511212	0.07658198495	0.2205
WOA	1.40414979085	3.22870683572	1.89761687251	0.47546784469	0.0442
MSGO	1.78143056637	4.78551641462	2.48256475659	0.61409765208	0.0411

computational times of the 30 independent runs for all the fifteen algorithms is shown in Table 13.

3) CANTILEVER BEAM DESIGN

A detailed description of the objective function, constraint functions and the range of the decision variables (mathematical formulation) for the cantilever beam design is shown in Table 36 (**Appendix**). The best fitness values and their corresponding optimal decision variables for all the sixteen algorithms sorted in the ascending order of their fitness scores are given in Table 37 (**Appendix**). A comparative tabulation of the best, worst, average, standard deviation and the average computational times of the 30 independent runs for all the fifteen algorithms is shown in Table 14.

4) TENSION/COMPRESSION SPRING DESIGN

A detailed description of the objective function, constraint functions and the range of the decision variables (mathematical formulation) for the tension/compression spring design is shown in Table 38 (**Appendix**). The best fitness values and their corresponding optimal decision variables for all the sixteen algorithms sorted in the ascending order of their fitness scores are given in Table 39 (**Appendix**). A comparative tabulation of the best, worst, average, standard deviation and the average computational times of the 30 independent runs for all the fifteen algorithms is shown in Table 15.

5) 10-BAR TRUSS DESIGN

A basic description of the 10-bar truss design problem and its constraints is provided in Table 40 (**Appendix**). The best fitness values and their corresponding optimal decision variables for all the sixteen algorithms sorted in the ascending order of their fitness scores are given in Table 41 (**Appendix**). A comparative tabulation of the best, worst, average, standard deviation and the average computational times of the 30 independent runs for all the sixteen algorithms is shown in Table 16.

TABLE 15. Tabulation of best, worst, average (mean), standard deviation and the average computational times (seconds) for the tension/compression spring design from the 30 independent runs for the sixteen algorithms.

Algorithms	Best	Worst	Mean	Standard Deviation	Average Computational Time
ME-SGO	0.012665233	0.012950610	0.012683911	5.62E-05	0.2390
L-SHADE	0.012665234	0.013210065	0.012693972	9.77E-05	0.3078
MPEDE	0.012669158	0.012732363	0.012710457	2.41E-05	0.3499
SGO	0.012667381	0.012849562	0.012743586	4.56E-05	0.0792
GWO	0.012703978	0.013105946	0.012776107	1.04E-04	0.0707
ISGO	0.012665260	0.013311909	0.012804912	1.74E-04	0.0764
GABC	0.012715319	0.013456150	0.012864619	2.02E-04	0.0987
MEGWO	0.012678741	0.013308462	0.012880697	2.05E-04	0.0803
CLPSO	0.012740981	0.013506243	0.012980271	2.55E-04	0.1346
EPSO	0.012713094	0.017773158	0.013066680	9.37E-04	0.6649
ChOA	0.012842115	0.016108193	0.013348314	8.22E-04	0.1870
HSWOA	0.012754221	0.016406911	0.013372694	7.73E-04	0.0876
SMA	0.012670057	0.017332469	0.013386007	1.24E-03	0.1875
HSWOA+	0.012732026	0.018002269	0.013392215	1.27E-03	0.0764
WOA	0.012666503	0.016159385	0.013851240	1.22E-03	0.0686
MSGO	0.040992332	0.055436222	0.038567351	1.38E-02	0.0609

TABLE 16. Tabulation of best, worst, average (mean), standard deviation and the average computational times (seconds) for the 10-bar truss design from the 30 independent runs for the sixteen algorithms.

Algorithms	Best	Worst	Mean	Standard Deviation	Average Computational Time
MPEDE	5060.87043842	5076.85171483	5064.02430884	6.32510045	7.537
L-SHADE	5061.76661402	5086.54104024	5064.84893749	5.80737449	5.289
SMA	5061.36974029	5096.29515197	5068.92952786	8.74637144	11.069
ME-SGO	5061.30193860	5097.88968419	5084.88836938	15.58404217	5.522
GWO	5076.25174080	5126.66395695	5102.48545541	14.82826204	3.234
GABC	5089.66807074	5120.38270830	5105.69242847	10.06191397	3.384
ChOA	5147.70383078	5907.78738096	5290.05916403	250.09255479	3.677
CLPSO	5152.70055304	5500.63087888	5312.63888940	98.76338549	3.366
EPSO	5061.43035403	7349.14601502	5617.69634993	770.83793324	20.811
MEGWO	5345.13649658	6540.48118227	5956.22363164	485.31699972	3.314
HSWOA+	5130.60179834	7364.67647008	6042.53807980	631.85260498	21.420
WOA	5884.73096069	8155.58242175	6831.70270668	569.62933788	3.213
HSWOA	6244.40954659	8026.53898200	7027.51573342	474.01932446	18.622
SGO	5552.86358591	8408.39489218	7315.13903170	639.22578141	18.237
ISGO	6504.33958450	8552.95753299	7387.69461236	490.32316101	18.315
MSGO	6909.09280613	16619.02865276	9284.58726025	2176.71159957	18.489

Analysis of Results:

1) The performance of ME-SGO has been good for the standard engineering problems for all the five engineering problems with excellent performances for SE1, SE3 and SE4.
2) The difference between the state-of-the-art optimizers such as L-SHADE and MPEDE has been minimal with the three of them dominating for the five problems.
3) Compared to SGO and its other variants, ME-SGO achieved better solutions with higher accuracy and robustness through the testing with lower standard deviation rates. The distance-based strategy adaption and adaptive control parameters have been at the forefront in steering ME-SGO to improve the solution quality while not compromising on the computational times.
4) The performance of ME-SGO for the 10-bar truss optimization is indicative of its efficiency at balancing global and local exploration while SGO and its variants have not been able to achieve the same efficiency at delivering the optimal solution. The lower standard deviation by ME-SGO demonstrated the robustness of ME-SGO at handling optimization problems with multi-constated higher dimensionality.

V. INVESTIGATION OF THE PROPOSED METHOD FOR EV OPTIMIZATION PROBLEMS

To demonstrate the effectiveness of the proposed algorithm towards the handling of complex real-world constrained problems with multiple equality and inequity constraints and higher problem dimensions, four problems on EV optimization from the recent literature have been considered. The same algorithms are chosen with the previously set configurations for the algorithm tuning settings and a comprehensive comparative analysis is provided below.

A. PROBLEMS CONSIDERED FOR INVESTIGATION

Four complex problems namely, (i) the optimal power flow problem with EV loading for IEEE 30 bus system (9 Cases) and IEEE 57 bus-system (9 cases), (ii) optimal reactive power dispatch with uncertainties in EV loading and intermittencies with PV and Wind energy systems for IEEE 30 bus

TABLE 17. Summary of the case studies of the OPF for the IEEE 30 and IEEE 57 bus systems with EV loading.

Case Studies	Objectives of various case studies					
	Basic Fuel Cost	Voltage Stability	Emission	Power Loss	Voltage Deviation	Valve-point Effect
Case 1	✔					
Case 2		✔				
Case 3			✔			
Case 4				✔		
Case 5	✔					✔
Case 6	✔			✔		
Case 7	✔				✔	
Case 8	✔	✔				
Case 9	✔		✔	✔	✔	

system (25 scenarios), (iii) dynamic EV charging optimization (3 cases) and (iv) energy efficient control of parallel hybrid electric vehicle (3 cases with 2 scenarios) coverage the domains of power systems, energy and control optimization have been considered for validation through the proposed multi-strategy ensemble method and fifteen of the previously described state-of-the-art advanced and modern algorithms. The constraint handling for the first and second problems on EV optimization is done through the superiority of feasible solution method [52] and for the third and fourth problems, static penalty approach is followed.

1) EV LOADING MODEL

The EV loading model in the current work for the first and second problems is accomplished considering the additional electric power demand due to multiple Plug-in electric vehicles (PEVs) on the electric distribution system. The PEV loading model from [53] implemented for an IEEE 33 bus system for the optimal integration of distributed generators has been considered for the IEEE 30 bus system and extended to the IEEE 57 bus system in the current work. The EV loading models for the first and the second problems is formulated based on the average loading with considerations for the peak loading scenarios and off-peak conditions of EV load demand with respect to the varying load pattern of the distribution network. It is also assumed that the entire EV load is distributed on the residential busses. A detailed description of the EV loading is given the upcoming sub-sections and the summarization of the IEEE 30 and IEEE 57 bus systems with EV loading is provided in Table 42 (**Appendix**) and Table 43 (**Appendix**) respectively.

The third problem studies the effect of varying levels of EV loading from [55] with three scenarios of 100, 200 and 300 EVs. The probability distributions of the EVs connecting and disconnecting from the local grid is modelled using normal distribution and have initial SoC values specified by normal distributions within the range 0.1 to 0.9.

2) UNCERTAINTY WITH WIND AND PV ENERGY

The second problem considers the optimal reactive power dispatch from [54]. The EV loading model from the first problem based on [53] for the IEEE 30 bus has been followed here as well with 25 different scenarios investigated considering the uncertainties with the renewable power generation and load demand including EV loading. The base case considers 100% loading (fixed) of the network with 5% EV load followed by 24 randomized scenarios from a total of 1000 plausible scenarios formulated through Monte Carlo simulations obtained through the method of scenario reduction using backward reduction algorithm (BRA) [54].

3) SOLUTION METHODOLOGY

The MATPOWER (version 7.1) has been utilized in conjuncture with MATLAB R2020b and Backward/forward sweep based load flow has been used for load flow studies for the first and second problems on EV optimization [53].

B. OPTIMAL POWER FLOW PROBLEM WITH EV LOADING

The first problem is that of the optimal power flow (OPF) with EV loading for the standard IEEE 30 and IEEE 57 bus systems for several OPF objectives such as cost, emission, power loss, voltage stability etc. from [52] is considered. OPF is a highly non-linear complex optimization problem where the steady-state parameters of an electrical network need to be determined for its economical and efficient operation. The complexity of the problem escalates with the ubiquitous presence of constraints in the problem. Solving OPF remains a popular but challenging task among power system researchers. In the last couple of decades, numerous evolutionary algorithms (EAs) and swarm intelligence-based optimization algorithms have been considered to find optimal solutions with different objectives of OPF.

The nine different cases in the OPF for the IEEE 30 and IEEE 57 bus systems with EV loading are given in Table 17.

The OPF with EV loading for IEEE 30 bus system has 24 control/decision variables and the IEEE 54 bus system has 33 control variables to be optimized. The different cases for the formulation of the objective function and the various constraints are provided in Table 44 (**Appendix**). Summarization of the bus systems is provided in Table 45 (**Appendix**) and Table 46 (**Appendix**) for the IEEE 30 and IEEE 57 bus systems respectively. The lower and upper bounds for the optimization are given in Table 47 (**Appendix**).

1) OPF WITH EV LOADING FOR IEEE30 BUS SYSTEM

The procedure for EV loading from [53] has been followed with EV load distributed on the residential buses (17 buses for the IEEE 30 bus system).

To study the effect of additional electric power demand due to PEVs in the electric distribution system for IEEE 30 bus system, it has been assumed that 50 PEVs per residential bus with a total of 17*50 = 850 PEVs have been considered, where 45% of these PEVs are low hybrid vehicles equipped with 15 kWh batteries, 25% PEVs are medium hybrid vehicles with 25kwh batteries and 30% PEVs are pure battery vehicles with 40 kWh batteries. It is also assumed that all the electric vehicles return to the home with an SoC of 50%. Therefore, total electric demand due to PEVs per residential bus per day is 50*(15*45% + 25*25% + 40*30%)*0.5 = 625 kW and total electric demand needed per day due to PEVs is $625 * 17 = 10{,}625$ kW.

The tabulation of the best solutions with statistical analysis and computational times of OPF for the IEEE 30-bus system with EV loading for all the algorithms in comparative analysis is given in Table 18. The decision variables for the best performing algorithm for all the 9 cases are given in Table 47 (**Appendix**).

In Table 18, Fit denotes the fitness value, FC denotes the cost of fuel in $/h, E denotes emissions in t/h, P Loss denotes the real power loss in MW, VD denotes the voltage deviation in p.u., L-index denotes the L-index (max).

Analysis of Results:

1) ME-SGO obtained the optimal solutions for five out of the nine cases and for the other cases, the performance was quite competitive.
2) The first case saw competitive results from GABC, EPSO, MPEDE, MEGWO and ME-SGO. It is also worth noting that ME-SGO and MPEDE had the least standard deviation for this case. The second, third and sixth cases saw similar results with excellent performances from ME-SGO, MPEDE and EPSO.
3) The adaptive and multi-population approaches have been successful at handling the multiple constraints while delivering solutions with higher accuracy and the same performance has not been reflected with the other modern meta-heuristics.
4) MPEDE and EPSO performed second to the proposed method while L-SHADE and G-ABC performed next to them.
5) ChOA and MSGO performed poorly due to a lack of balance between exploration and exploitation. The re-initialization system in MSGO could not aid the exploitation system as the algorithm was slower to exploit the promising regions as indicated by the results. The computational times for ChOA have been the highest due to the integration of chaotic sequences.

2) OPF WITH EV LOADING FOR IEEE57 BUS SYSTEM

The procedure for EV loading from [53] has been followed with EV load distributed on the residential buses (41 buses for the IEEE 57 bus system).

To study the effect of additional electric power demand due to PEVs in the electric distribution system for IEEE 57 bus system, it has been assumed that 100 PEVs per residential bus with a total of 41*100 = 4100 PEVs have been considered, where 45% of these PEVs are low hybrid vehicles equipped with 15 kWh batteries, 25% PEVs are medium hybrid vehicles with 25kwh batteries and 30% PEVs are pure battery vehicles with 40 kWh batteries.

It is also assumed that all the electric vehicles return to the home with a SOC of 30%. Therefore, total electric demand due to PEVs per residential bus per day is 100*(15*45% + 25*25% + 40*30%)*0.7 = 1750 kW and total electric demand needed per day due to PEVs is 1750*41 = 71,750 kW.

The tabulation of the best solutions with statistical analysis and computational times of OPF for the IEEE 30-bus system with EV loading for all the algorithms in comparative analysis is given in Table 19. The decision variables for the best performing algorithm for all the 9 cases are given in Table 48 (**Appendix**). In Table 19, Fit denotes the fitness value, FC denotes the cost of fuel in $/h, E denotes emissions in t/h, P Loss denotes the real power loss in MW, VD denotes the voltage deviation p.u., L-index denotes the L-index (max).

Analysis of Results:

1) The performance of ME-SGO has been similar to that of the IUEEE 30 bus system with it being consistent at delivering a balanced performance for complex landscapes. ME-SGO performed well for 6 out of the 9 vases for the IEEE 57 bus system.
2) GABC performed next to the proposed method followed by EPSO and MPEDE. It is inferred that multi-population and multi-strategy-based paradigms have been dominant at delivering a consistent performance while static control strategies have found it challenging to explore and exploit simultaneously through the search process.

3) OPTIMAL REACTIVE POWER FLOW FOR IEEE 30 BUS SYSTEMS WITH UNCERTAINTY IN LOADING AND RENEWABLE POWER GENERATION CONSIDERING EV LOADING

The second problem on EV optimization is that of the optimal reactive power dispatch (ORPD) from [54] accounting for the uncertainties with EV loading and distribution system demands, uncertain renewable power i.e., wind and PV power. The load uncertainty model is based on the probability density function (PDF) from [54] and Weibull PDF describes the wind speed distribution. 1000 Monte Carlo scenarios for the loading and windspeed distributions are simulated and 25 most probable scenarios have been considered. IEEE 30 bus system with 25 scenarios with the EV loading model from Problem 1 is used. A detailed description of the mathematical

TABLE 18. Tabulation of the best solutions with statistical analysis and computational times of OPF for the IEEE 30-bus system with EV loading for all the algorithms in comparative analysis.

Case 1		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	846.00	851.379	842.7941	842.8111	843.1834	842.4997	840.8165	841.9357	850.1264	842.8518	840.0881	839.1136	839.1415	839.1599	839.9184	**838.9998**
	FC	845.9995	897.224	842.7941	922.9688	851.0768	842.652	840.7908	904.8547	853.7814	868.2758	840.0881	839.5686	839.1417	839.4001	840.2603	**839.0224**
	E	0.365038	0.725274	0.364381	0.22964	0.416912	0.354828	0.369406	0.707223	0.317653	0.401458	0.382387	0.378853	0.381327	0.371796	0.386563	**0.380702**
	P Loss	10.4123	19.44098	9.684598	5.19809	12.48481	9.020405	9.534648	21.86486	8.466397	10.80151	9.83605	9.600021	9.543881	9.404811	9.776321	**9.49952**
	VD	0.608065	1.374786	0.637967	0.901473	0.777234	0.588613	0.480663	1.270472	0.504399	0.355607	0.650101	0.496043	0.905726	0.601455	0.339746	**0.872397**
	L-index	0.152553	0.164938	0.141102	0.150195	0.159567	0.141812	0.14901	0.16313	0.150537	0.155913	0.154506	0.147813	0.140047	0.14377	0.146945	**0.140281**
Worst		849.2907	1059.5315	849.8282	853.1004	928.0401	869.3596	858.6807	858.8673	960.451	848.2539	842.2256	839.9647	843.3792	839.3656	841.1855	**839.0894**
Mean		847.8646	995.6719	845.2318	847.9886	872.6297	856.6636	849.1835	847.6339	926.716	845.1453	841.317	839.322	840.2555	839.2249	840.6835	**839.0626**
Std.		1.323248	159.275	2.733927	3.750684	37.2497	11.29628	6.408723	6.873694	916.9501	2.155616	0.881999	0.364586	1.79989	0.084277	0.471981	**0.024449**
Avg. Time		76.74614	75.35418	95.28828	77.06109	76.63067	87.14379	97.09069	114.64403	106.56940	88.97466	97.60864	73.68705	103.24306	79.27807	64.68234	**78.69122**
Case 2		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	0.140238	5.154001	0.139911	0.141577	0.141878	0.140605	0.14042	0.140506	0.81915	0.140687	0.139454	0.14073	0.140533	**0.139465**	0.140332	0.139812
	FC	972.3689	883.1619	888.0677	870.1798	938.5162	880.3212	907.7723	860.3001	897.375	879.5503	923.1893	945.2026	878.7784	**914.7841**	893.6888	864.7808
	E	0.213919	0.635693	0.264132	0.435438	0.266644	0.251336	0.252479	0.340031	0.262363	0.28102	0.263954	0.236746	0.341194	**0.264215**	0.257877	0.367517
	P Loss	4.10844	18.31727	6.403909	14.30844	6.154964	6.466715	6.073045	8.950745	7.033266	7.14045	6.630546	5.850191	8.866962	**6.809632**	6.709671	8.95387
	VD	0.750277	1.357374	0.79802	1.113533	0.253067	0.74133	0.59773	0.732463	0.626344	0.481557	0.773265	0.554557	0.606568	**0.87015**	0.460169	0.872247
	L-index	0.140238	0.164514	0.139911	0.161306	0.148939	0.140146	0.140419	0.140412	0.155354	0.152408	0.139884	0.145356	0.140524	**0.13955**	0.141438	0.139958
Worst		0.143887	8.128944	1.824919	0.148657	0.149159	0.141501	0.150093	0.143408	2.157401	0.142087	0.141785	0.143329	0.141473	**0.140318**	0.141408	0.140514
Mean		0.142228	7.521037	0.480964	0.143051	0.145275	0.141199	0.144379	0.141758	1.741884	0.141464	0.140726	0.141725	0.141119	**0.139866**	0.140901	0.140053
Std.		0.001642	2.061549	0.745774	0.003134	0.002841	0.000356	0.003608	0.001301	0.954918	0.000519	0.000924	0.000973	0.000408	**0.000311**	0.000468	0.000382
Avg. Time		75.78222	74.65869	93.21251	75.14979	75.07077	78.07716	80.12519	129.779	174.4318	87.61731	199.2763	74.8331	217.2891	**159.0977**	63.72522	79.45147
Case 3		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	0.214231	8.228349	0.219793	0.209719	0.208951	0.220248	0.208789	0.212696	0.27579	0.213123	0.209109	0.208769	**0.208744**	0.208748	0.297011	0.208774
	FC	969.7238	897.3902	967.6307	867.1108	933.5113	947.6574	974.9315	897.6064	909.348	923.174	983.2972	985.7148	**980.4872**	980.6407	896.8287	980.257
	E	0.214231	0.72567	0.219793	0.507172	0.22308	0.220917	0.209821	0.726186	0.255167	0.24957	0.209109	0.209291	**0.208744**	0.208767	0.238701	0.208734
	P Loss	5.096559	19.48416	4.617802	16.03924	6.050764	4.781059	3.894808	19.54034	6.208979	6.28473	4.534064	4.973743	**3.629422**	3.684992	6.703492	3.606105
	VD	0.387082	1.375456	0.467958	1.159756	1.263273	0.328949	0.549713	1.454088	0.534656	0.287089	0.340167	0.473036	**0.822999**	0.655815	0.236689	0.903189
	L-index	0.158808	0.16381	0.151531	0.161813	0.162512	0.144346	0.149121	0.165655	0.153586	0.150582	0.14948	0.154709	**0.141495**	0.143852	0.15397	0.140792
Worst		0.274760	8.556144	0.240337	0.224023	0.255691	0.302704	0.319833	0.230943	3.869485	0.228218	0.213434	0.208891	**0.225422**	0.208767	0.303756	0.208957
Mean		0.229546	8.387805	0.232081	0.214856	0.218795	0.254127	0.254861	0.221917	2.609668	0.223725	0.214032	0.208818	**0.21236**	0.20876	0.298922	0.208872
Std.		0.025442	0.518051	0.009205	0.006753	0.020628	0.036042	0.040837	0.007145	1.053006	0.006062	0.009742	5.15E-05	**0.007318**	7.61E-06	0.002825	6.82E-05
Avg. Time		138.38500	150.77890	177.52918	145.12104	145.71301	150.09114	153.17129	190.36315	171.38312	139.27421	194.68714	148.57214	**201.30660**	157.98909	133.01630	146.00101
Case 4		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	5.553741	8.94997	4.074181	3.877234	3.873018	4.52239	5.753958	4.110825	6.553419	4.54532	3.576668	3.533186	3.542473	3.529788	5.092266	**3.513195**
	FC	927.0897	890.221	982.3011	923.1866	949.1163	956.5536	901.8779	897.6042	871.1775	881.6896	994.398	994.7143	994.5315	994.4689	940.1532	**994.3924**
	E	0.227562	0.669293	0.213487	0.229271	0.223327	0.225823	0.256311	0.726181	0.270917	0.26823	0.209642	0.209659	0.209637	0.20966	0.225763	**0.209634**
	P Loss	5.553741	18.47003	4.074181	6.612002	6.084084	4.52239	5.746655	19.53976	7.005108	7.788369	3.582275	3.616495	3.542463	3.550141	4.643554	**3.514513**
	VD	0.378849	1.354075	0.433619	0.952843	0.862492	0.576898	0.408282	1.45363	0.520312	0.471739	0.837178	0.81785	0.877235	1.008291	0.286608	**0.881501**
	L-index	0.157839	0.164324	0.154266	0.158503	0.158111	0.145706	0.151916	0.165649	0.148067	0.162735	0.140139	0.140785	0.139968	0.140624	0.150138	**0.140809**
Worst		6.936551	9.155603	5.526557	5.656269	4.127091	9.309694	9.247071	6.73537	9.192385	5.386695	4.761731	3.596305	3.887071	3.575087	7.437347	**3.640378**
Mean		6.071761	7.567082	4.969309	4.476482	4.004234	7.246033	7.30909	5.274029	8.8103485	5.100594	4.190827	3.578142	3.675719	3.542276	6.800815	**3.545532**
Std.		0.528554	1.315007	0.569346	0.751704	0.101996	1.775808	1.46054	1.080752	748.6969	0.36308	0.544878	0.025574	0.175327	0.019282	0.516903	**0.053079**
Avg. Time		153.81099	160.13538	191.99149	170.20624	160.14499	153.47309	154.11508	191.00458	164.30966	160.14838	213.89953	155.78886	202.29368	163.93187	131.32616	**164.53972**
Case 5		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	878.2331	2480.159	881.6142	885.2875	887.0241	893.655	884.8203	879.5134	1022.117	887.2792	877.8526	875.7404	873.852	873.3601	877.0551	**872.8843**
	FC	843.7821	895.2583	845.4233	877.5124	854.594	844.9668	850.1421	845.5223	866.6872	887.9042	845.9232	848.2295	843.5619	844.546	843.6492	**842.6901**
	E	0.43019	0.699295	0.4249	0.56969	0.407602	0.357795	0.43089	0.432633	0.31444	0.342889	0.438726	0.428809	0.442188	0.44175	0.429063	**0.442874**
	P Loss	10.82281	19.07844	11.30924	17.44683	14.1357	9.152594	10.5186	11.40857	8.24158	12.42575	11.61989	11.84344	11.3461	11.52565	10.64742	**11.11823**
	VD	0.625333	1.331995	0.564282	1.185552	1.443495	0.383557	0.522245	0.405687	0.455104	0.501561	0.205982	0.230899	0.502686	0.526654	0.386179	**0.650641**
	L-index	0.146574	0.164519	0.157914	0.162681	0.171533	0.147378	0.152434	0.151266	0.150231	0.155739	0.148751	0.150646	0.152654	0.144771	0.153781	**0.142891**
Worst		901.9726	18023.3	913.4064	903.5731	949.3066	905.7523	971.5128	908.4545	3712.405	891.5864	902.4197	879.1579	880.6285	874.6974	890.2143	**873.7989**
Mean		891.3593	7371.405	895.1541	892.2354	911.8736	899.7542	906.6605	893.0876	2716.593	889.3661	885.6593	877.4574	876.1877	873.925	882.5018	**873.4211**
Std.		8.492575	6410.772	14.28205	7.447905	31.05046	4.64662	36.5684	10.87556	1116.146	1.892651	9.790751	1.39814	2.870063	0.521496	5.098621	**0.231754**
Avg. Time		155.69908	164.73543	198.54402	161.29712	159.05008	154.63217	150.96084	199.37580	209.91275	166.94579	211.95170	159.09875	215.53678	172.59082	134.75815	**160.93747**
Case 6		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	1128.046	1493.714	1113.637	1120.257	1108.408	1115.91	1126.571	1100.085	1887.871	1120.71	1097.938	1096.191	1095.911	**1095.754**	1099.743	1095.933
	FC	918.4876	897.1196	882.387	862.9262	883.5738	891.6	914.6384	915.9175	924.5733	869.4005	902.7166	896.7816	899.0619	**900.2565**	894.8093	899.9919
	E	0.233298	0.725025	0.246338	0.307839	0.2553	0.258511	0.233552	0.390033	0.266252	0.314905	0.233235	0.234229	0.233154	**0.232734**	0.237519	0.232652
	P Loss	5.238967	19.41386	5.781239	10.68896	8.357056	5.651715	5.295126	24.82199	7.036815	8.685024	4.883755	5.002323	4.921244	**4.913702**	5.327726	4.869358
	VD	0.338801	1.352374	0.542644	1.027756	0.962487	0.378745	0.395465	0.843099	0.566564	0.421056	0.715838	0.904244	0.896749	**0.822314**	0.392368	0.899778
	L-index	0.150313	0.164238	0.155305	0.15986	0.15888	0.151419	0.154069	0.154125	0.143149	0.141692	0.142788	0.141508	0.140141	**0.141016**	0.147623	0.140761
Worst		1132.415	21112.37	1137.426	1156.053	1131.947	1175.594	1185.724	1140.818	4256.966	1155.381	1144.093	1100.13	1123.851	**1097.98**	1102.494	1096.343
Mean		1129.197	8388.232	1122.948	1140.316	1122.975	1153.719	1149.32	1113.946	2638.21	1134.865	1109.151	1098.929	1110.191	**1097.071**	1098.658	1095.177
Std.		1.866431	7563.069	10.32187	13.64884	9.649766	24.22352	23.30294	15.63412	977.107	12.96544	19.61783	1.62284	12.38155	**0.909251**	9.370119	0.937232
Avg. Time		158.25576	162.94180	200.87973	157.69825	159.69406	150.08374	148.74970	198.66797	227.96105	161.96093	209.02621	147.16739	214.25765	**173.72671**	126.24888	164.54502
Case 7		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	860.134	865.1773	859.3909	859.8883	863.2451	870.2179	864.0402	858.7172	1625.613	866.2138	856.9671	853.7211	855.9981	853.7802	854.3421	**852.2779**
	FC	844.8677	896.817	844.2298	857.2582	860.0125	852.1852	843.0093	890.1402	927.7239	853.1512	842.2838	839.8856	842.4945	842.7819	840.1487	**842.1262**
	E	0.356156	0.724304	0.346875	0.425675	0.448202	0.391203	0.34725	0.588346	0.261637	0.353399	0.383038	0.387684	0.382459	0.39314	0.384003	**0.378727**
	P Loss	9.839039	19.33522	9.034261	14.77547	14.57348	10.56138	9.159174	19.04348	6.330321	9.537768	10.35935	9.817566	10.41775	10.82199	9.844267	**10.29822**
	VD	0.37093	1.279476	0.433365	1.149201	1.677211	0.18343	0.335666	0.435745	0.500875	0.306753	0.148792	0.786975	0.135046	0.117268	0.38895	**0.116209**
	L-index	0.152673	0.163348	0.151847	0.161777	0.190473	0.148214	0.144819	0.15802	0.151987	0.153573	0.148576	0.142611	0.150324	0.149365	0.143345	**0.150708**
Worst		872.9651	16464.89	867.2975	1455.96	974.762	885.0054	875.065	885.8723	4187.432	878.0909	863.1857	855.8024	871.516	856.3639	857.9126	**853.3646**
Mean		866.3962	8060.087	861.9589	981.9235	898.328	880.3477	870.6265	867.4616	2657.564	872.6355	859.1409	854.6916	861.2388	854.6024	855.4953	**853.0805**
Std.		5.343617	5722.306	3.228853	265.0171	46.04899	5.855914	4.217623	11.02671	1052.701	4.257293	2.607437	0.754186	6.191362	1.092911	1.427915	**0.295509**
Avg. Time		168.61468	158.34312	200.23106	150.94981	149.92205	148.62123	146.02795	189.51954	215.66227	162.67874	197.31512	143.90148	217.03204	162.02432	120.75938	**183.94840**
Case 8		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	868.1086	1758.232	873.484	870.4453	881.827	862.0318	857.2719	855.8243	891.0266	857.5705	853.4199	856.4779	853.8629	853.1719	858.9532	**852.9959**
	FC	848.3919	896.5817	845.3992	855.485	857.0836	848.0405	842.8998	842.1831	889.1861	881.7165	839.4223	842.5438	839.8343	839.3996	845.434	**839.0393**
	E	0.341221	0.720392	0.341877	0.348847	0.382133	0.355344	0.363693	0.35512	0.3225	0.292844	0.375613	0.369946	0.384726	0.371966	0.337135	**0.380442**
	P Loss	9.552348	19.31857	9.665467	11.05721	13.16475	9.273211	9.105654	9.171764	7.092829	10.86089	9.442264	10.07285	9.760312	9.338523	9.182169	**9.503517**
	VD	0.197167	1.326935	0.281526	0.8172	1.04979	0.418872	0.658484	0.649862	0.431722	0.47805	0.847769	0.563992	0.687221	0.785433	0.182927	**0.90461**
	L-index	0.150133	0.164049	0.157047	0.157457	0.160545	0.143324	0.140972	0.144174	0.151942	0.140796	0.140438	0.157606	0.140291	0.139672	0.147276	**0.139828**
Worst		896.9414	15045.45	952.2177	884.1884	936.5959	870.5104	861.0883	864.1067	2106.045	873.971	900.7776	862.209	855.7358	853.7093	867.4337	**853.1502**
Mean		878.5383	7699.034	905.128	875.3479	905.6385	866.6979	859.6046	858.9434	1528.46	862.2128	865.5607	858.0465	854.5286	853.4467	861.9657	**853.1092**
Std.		11.38318	5584.911	30.61322	5.23184	19.6751	3.576969	1.445954	3.743219	504.4051	6.750243	19.83904	2.383648	0.845406	0.243385	3.231067	**0.036962**
Avg. Time		74.19102	74.80112	91.81312	76.03192	77.84499	148.12306	156.09400	179.39091	201.15003	163.01751	207.65160	73.91391	223.53320	164.73050	64.26668	**79.27672**
Case 9		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	1031.752	1017.552	1932.036	1029.952	1026.04	1035.309	1029.85	1016.333	1187.342	1027.402	1015.696	1013.738	1018.537	**1013.00**	1071.75	1013.102
	FC	877.3133	866.2665	897.1909	863.473	860.1092	861.0235	882.0869	933.3023	988.3316	857.408	870.9711	880.9986	873.4487	**871.4625**	858.8177	870.15
	E	0.258411	0.262029	0.725195	0.313017	0.291676	0.290263	0.258007	0.221686	0.211667	0.311735	0.255679	0.248655	0.255697	**0.255242**	0.287395	0.258022
	P Loss	6.461801	6.280038	19.43238	10.50576	8.745068	7.423596	6.070226	4.690929	4.664247	7.918642	6.042255	5.955475	6.16131	**5.931483**	7.083063	5.943143
	VD	0.350914	0.387934	1.370132	0.927805	0.793445	0.304102	0.444464	0.723901	0.397814	0.37637	0.341718	0.32733	0.222992	**0.334295**	0.328065	0.302762
	L-index	0.156919	0.151347	0.164593	0.15877	0.153892	0.148218	0.149714	0.149709	0.145055	0.151331	0.149428	0.148652	0.14965	**0.148688**	0.144913	0.14962
Worst		1052.332	1038.087	11128.29	1058.965	1067.895	1058.819	1047.698	1041.574	2607.641	1048.247	1063.904	1017.07	1031.198	**1014.469**	1080.307	1014.43
Mean		1038.564	1028.932	6729.397	1042.631	1049.375	1043.91	1037.244	1023.745	2026.854	1033.374	1032.355	1015.736	1023.742	**1013.643**	1074.335	1013.622
Std.		8.310502	7.352866	4467.315	11.72958	17.4982	9.801351	7.508635	10.29596	672.3382	8.631743	18.75465	1.350849	5.073422	**0.529019**	3.519092	1.100531
Avg. Time		159.09949	193.58818	154.05176	152.56939	142.63854	167.19561	154.40044	198.15335	248.91338	170.52744	197.55572	147.68027	213.85650	**158.82472**	120.83944	167.61422

modelling, scenario modelling etc. are available at **Appendix**. The constraints have been the same as described in Problem 1 and the constraint handling mechanism remains the same.

The formulation of the objective function for the two cases, i) Minimization of real power loss and ii) Minimization of voltage deviation is provided in Table 48 (**Appendix**).

TABLE 19. Tabulation of the best solutions with statistical analysis and computational times of OPF for the IEEE 57-bus system with EV loading for all the algorithms in comparative analysis.

Case 1		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	47090.5	115010.2	46364.7	46483.8	47481.9	49033.1	46401.2	48987.2	63858.7	51073.2	45130.6	45180.2	49056.1	44987.3	45342.3	**44879.3**
	FC	46242.59	134164.7	45833.16	140289.9	47212.1	47133.71	45040.92	48560.92	45249.53	46136.05	45137.58	45180.17	45221.16	45009.72	46080.43	**44915.54**
	E	1.453652	8.053042	1.410286	8.567442	1.567351	1.38718	1.773077	1.634094	1.861071	1.477945	1.598458	1.628544	1.710992	1.641273	1.480864	**1.512167**
	P Loss	20.17187	174.268	19.83188	186.7311	25.72846	19.25134	23.10664	32.74108	21.2422	22.91329	24.52422	22.62108	24.73187	21.69524	18.62161	**22.16468**
	VD	1.406834	2.825995	1.38134	2.916777	1.877069	1.612153	1.33714	1.323802	2.18973	1.486883	1.293693	1.294587	1.672443	1.285127	1.196973	**1.293303**
	L-index	0.37903	0.417674	0.377198	0.44385	0.375893	0.380455	0.3763	0.373603	0.393493	0.393102	0.382950	0.361098	0.359947	0.379477	0.378146	**0.373453**
Worst		59073.4	222062.7	94044.6	52760.1	54698.1	55425.4	48940.5	63878.9	92364.8	58866.8	45495.4	45961.7	69371.3	45415.4	46840.4	**44973.1**
Mean		51496.2	173773.3	59646.9	48848.2	51962.6	53027.6	47885.6	53743.0	75587.2	56239.4	45061.4	45437.6	59026.3	45194.9	45847.2	**44918.1**
Std.		4563.136	38429.76	19703.03	2342.403	2766.652	2660.451	1059.365	6355.929	11171.15	3199.117	905.2	307.0161	8724.053	164.8337	593.8976	**39.40538**
Avg. Time		169.7605	176.6597	204.8056	172.7428	173.538	181.4059	203.7693	210.0997	348.5163	101.6477	52.62	161.2724	219.4665	165.4529	144.243	**186.2052**
Case 2		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	30.0322	59.8535	35.8590	22.9254	65.8626	54.9227	19.5598	27.8715	75.1066	21.9833	17.3141	20.8635	23.3301	17.8393	23.7076	**16.1845**
	FC	51588.05	133778.3	61194.05	47803.77	47696.24	46456.42	46990.76	52260.13	59760.92	58998.4	47033.5	45679.51	59245.16	46124.34	57481.67	**45060.36**
	E	1.713413	8.041967	2.484898	1.801691	2.010015	1.674835	1.216049	1.660419	2.939638	1.870395	1.259756	1.569467	1.807923	1.397845	2.162117	**1.625308**
	P Loss	30.03222	174.9026	46.26557	24.78529	26.61039	24.9002	19.539	36.49298	43.57137	45.8009	26.5915	21.13611	43.3613	19.79394	38.64849	**25.15457**
	VD	1.279893	2.939145	1.473843	2.57813	2.093178	1.449744	1.415928	1.662238	2.214218	2.6745	1.6735	1.295223	1.97114	1.472072	1.272774	**1.449709**
	L-index	0.370784	0.442054	0.386525	0.484658	0.388629	0.384331	0.370729	0.376159	0.40333	0.39211	0.37942	0.364563	0.37592	0.366839	0.368753	**0.378041**
Worst		55.16476	99.40319	67.30893	42.82655	90.2439	85.86901	44.31852	45.4557	92.1285	35.9751	19.7317	31.5223	34.64768	19.21389	56.73801	**19.26557**
Mean		37.95052	75.3924	46.57177	28.81901	84.81551	64.58915	33.15924	36.98464	84.03333	26.5727	18.7692	24.9572	29.85312	18.51018	34.98646	**17.07139**
Std.		22.64826	41.8723	28.18099	19.53468	32.48402	20.63963	16.0351	19.4125	12.85514	14.9029	2.0991	10.31889	16.06642	1.353669	23.008	**1.466966**
Avg. Time		182.02	179.34	211.81	176.09	176.46	184.76	206.04	212.25	353.03	104.69	165.30	201.38	227.52	171.53	149.65	**237.84**
Case 3		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	1.584263	2.347749	1.637904	4.716206	2.486106	2.326635	1.535374	1.65505	2.38586	2.174092	1.145559	1.820006	**1.116403**	1.597811	1.276371	1.155284
	FC	48890.33	138998.9	50760.36	73126.72	45494.82	63004.4	45403.66	48758.85	57011.84	57487.7	47248.81	48650.56	**48351.9**	46596.08	55641.73	47838.37
	E	1.44926	8.460674	1.637904	3.272099	1.857599	2.35149	1.535389	1.656741	2.652791	1.947555	1.480697	1.855667	**1.116408**	1.485754	2.090685	1.12969
	P Loss	21.25115	183.643	24.25213	66.89155	25.59263	42.62748	20.11263	32.84056	42.17692	46.70873	23.621	25.52614	**20.20402**	20.79153	38.47429	18.3848
	VD	1.221416	2.963311	1.44331	2.313383	2.195809	1.068173	1.459121	1.431541	2.164381	1.843836	1.496539	1.168856	**1.561037**	1.647826	1.400673	1.198078
	L-index	0.381758	0.424362	0.378292	0.391116	0.389161	0.370686	0.377016	0.384123	0.400656	0.380166	0.382349	0.379038	**0.364649**	0.376823	0.382027	0.371551
Worst		3.871553	5.171925	4.452366	6.679223	5.148881	4.911068	5.470333	3.570854	4.341919	4.35771	2.334985	4.846499	**3.236296**	2.448925	2.606286	2.115909
Mean		3.07622	4.753459	3.212678	5.711154	3.24038	3.337047	4.521741	2.767805	3.674184	3.788256	1.611616	3.578712	**2.493817**	1.924228	1.961848	1.515651
Std.		1.789805	3.507365	1.910253	2.824249	2.43214	2.409467	3.330986	1.258408	2.455043	2.822602	0.459284	2.137514	**1.559347**	0.917704	1.01279	0.963511
Avg. Time		173.55	178.66	209.99	175.96	176.93	184.93	206.11	214.50	351.09	103.24	164.42	198.22	**230.23**	171.08	148.19	197.75
Case 4		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	48670.6	122928.7	49605.1	50232.8	49751.4	49271.1	47566.8	48926.2	65561.4	52684.9	47260.2	**46808.0**	48532.3	47000.8	47530.6	46905.3
	FC	46506.55	97615.31	46726.49	47257.6	47261.19	46872.56	45158.43	44916.66	47473.4	47590.28	45233.32	**45071.52**	45225.22	45008.0	46008.3	45040.09
	E	1.44246	5.238261	1.513071	1.484517	1.618087	1.596128	1.421257	1.556245	1.944545	1.591843	1.693077	**1.428393**	1.805315	1.625566	1.560156	1.420811
	P Loss	21.64009	108.6983	21.64523	22.865	25.05174	23.12586	19.72161	20.12882	22.47676	30.36122	20.33981	**21.30668**	23.6475	21.0545	19.20352	20.15759
	VD	1.439574	2.844386	1.102612	2.051375	2.172268	1.22607	1.273997	1.535769	2.284318	2.616786	1.337142	**1.393597**	1.698037	1.373977	1.434851	1.242456
	L-index	0.376203	0.425504	0.38145	0.364621	0.381959	0.369787	0.382437	0.378613	0.397218	0.416715	0.373134	**0.369802**	0.35744	0.375076	0.384662	0.372958
Worst		72572.3	237322.8	69637.1	60732.2	58980.4	57510.8	50845.3	52901.4	101130.1	60683.9	57326.8	**47887.2**	66524.0	50406.5	48967.6	48471.0
Mean		60701.1	181004.1	57034.2	57387.9	53473.4	53389.0	49411.5	50929.9	83011.6	55784.3	50629.2	**47419.0**	56823.9	48193.0	48159.8	47355.5
Std.		9919.429	45875.13	9096.789	4111.8	3695.228	3461.838	1624.754	1673.96	15800.89	3471.658	4275.382	**390.8797**	6568.65	1407.134	572.4356	746.7003
Avg. Time		235.05	261.31	283.61	257.90	263.35	270.57	305.91	311.95	524.06	151.21	285.61	**241.71**	332.64	247.20	221.20	256.10
Case 5		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	51435.9	141791.1	46701.2	47493.8	48076.9	46277.9	46528.7	47208.9	87144.6	50851.5	45695.6	45082.1	55449.1	45313.2	45941.8	**44990.1**
	FC	48107.4	129474.1	46553.42	48131.53	46527.57	46011.26	46324.97	46654.4	51183.12	55599.37	45522.76	45407.63	45510.6	45742.44	45401.7	**44899.31**
	E	1.521617	7.657626	1.382187	1.540015	1.685159	1.698608	1.460346	1.583475	2.23443	1.89572	1.727919	1.36341	1.788605	1.635294	1.636324	**1.487879**
	P Loss	22.19091	165.4258	18.33647	25.70182	30.35684	25.89103	22.61932	20.86886	31.86871	46.29041	23.19437	19.18309	24.11444	26.19838	23.47226	**21.46148**
	VD	1.575845	2.844244	1.284318	2.207762	1.381912	1.400939	1.430554	1.486759	2.303997	2.978235	1.523155	1.539392	1.938163	1.175802	1.29394	**1.320027**
	L-index	0.372872	0.437289	0.375636	0.381283	0.380255	0.372448	0.380509	0.373132	0.389861	0.422588	0.376115	0.367341	0.373185	0.376772	0.380136	**0.371187**
Worst		59397.4	203262.3	57912.1	54947.6	71352.5	52202.8	52161.9	53221.8	115786.3	64183.6	47112.8	45517.2	73784.4	45783.3	46682.5	**45826.0**
Mean		54523.8	169648.9	53775.5	49909.3	54570.3	49137.1	49100.4	50455.1	98296.8	58027.0	46432.9	45253.5	62958.5	45467.2	46351.8	**45212.1**
Std.		2990.063	24505.61	4240.638	3255.854	9720.825	2554.359	2281.52	2651.641	13395.83	4854.977	706.9567	166.1306	9716.819	183.1974	265.8783	**409.4793**
Avg. Time		231.93	266.29	309.50	263.71	256.14	272.45	309.49	321.64	520.52	153.25	288.00	245.22	328.76	247.85	217.89	**248.36**
Case 6		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	47474.1	105300.5	45765.3	45671.3	46378.1	49814.7	47216.5	47323.3	80601.9	50587.4	45553.6	45127.0	49603.5	45182.1	45818.3	**44956.5**
	FC	47332.44	121295.7	44979.8	51169.41	50143.98	47895.14	46044.18	47057.2	49933.87	54380.2	45258.6	45502.5	47377.56	45074.7	49555.12	**44857.83**
	E	1.815622	7.033547	1.449553	1.877232	1.882888	1.541269	1.475116	1.367982	2.16680	1.52811	1.76377	1.605782	1.200034	1.711811	1.44670	**1.45100**
	P Loss	26.89475	159.0813	21.39951	28.87124	27.7841	22.06131	19.92621	25.8620	29.0436	33.9974	23.6628	27.31383	18.9578	25.10935	24.00335	**21.35757**
	VD	1.416787	2.506798	1.283404	2.25081	2.1471	1.426042	1.39421	1.308156	2.34142	2.29961	1.43865	1.153169	1.613887	1.303191	1.256158	**1.274951**
	L-index	0.372245	0.441035	0.375275	0.389799	0.380525	0.381716	0.372098	0.381435	0.39329	0.44291	0.37282	0.37798	0.367412	0.367235	0.371882	**0.375976**
Worst		62987.5	180316.2	70984.3	54156.2	52402.2	61956.8	51287.5	51798.1	97973.6	63046.1	46686.2	47975.7	67137.4	45424.4	49153.5	**45183.7**
Mean		58021.7	148394.1	55258.8	49344.2	48913.4	52980.4	49048.4	49435.1	89084.5	55838.6	46383.0	45745.9	57352.8	45249.5	46814.8	**45039.5**
Std.		6737.604	35287.66	9901.876	3081.287	2223.012	5118.491	1764.901	1695.427	6486.714	5043.1	202.9	1248.029	8401.912	57.72317	1330.906	**105.8475**
Avg. Time		264.18	265.72	308.58	257.58	256.67	269.13	306.63	319.78	505.53	151.25	291.06	239.64	329.06	245.98	212.02	**263.02**
Case 7		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	52430.8	103175.2	48665.1	48610.8	50282.9	48604.6	45973.5	47537.1	63602.5	52456.7	45969.1	**44905.5**	56022.0	45072.3	45688.0	44914.9
	FC	49136.892	128475.841	47039.605	63402.201	46032.461	47596.034	45919.858	46291.792	49564.711	69167.833	45949.519	**45165.958**	47582.172	45159.838	45595.929	44868.46
	E	1.4974221	7.62654753	1.4813886	2.554184	1.4764533	1.706522	1.4456519	1.4767864	2.1744233	2.6911265	1.5884438	**1.7173888**	1.2495829	1.7104115	1.5280845	1.51531
	P Loss	24.37322	165.907912	18.575179	50.321316	23.590073	29.164869	19.567665	21.432282	29.769652	68.000086	23.924689	**27.093766**	21.571937	27.503934	20.810063	20.648351
	VD	1.3035133	2.61880175	1.8025118	2.3099044	2.330449	1.4214223	1.2397036	1.5107243	2.1775215	1.6944507	1.2039229	**1.6749556**	1.9427552	1.3711188	1.1323834	1.5308575
	L-index	0.3676725	0.42991643	0.3784037	0.396772	0.3846547	0.3707335	0.3872429	0.3679003	0.4051225	0.376428	0.3770062	**0.370031**	0.377474	0.3686529	0.3775691	0.3876748
Worst		91020.9	176095.9	69423.3	63304.8	67572.5	60873.9	48360.3	52868.8	80743.2	61753.8	49154.5	**46555.2**	67908.2	45485.7	48636.2	44988.0
Mean		67345.0	143436.4	56897.2	55445.0	54709.3	53968.7	47144.1	49394.6	70972.2	55426.3	47865.5	**45505.3**	62480.8	45202.3	47200.4	44944.7
Std.		14906.482	30422.1844	7760.1553	6148.5291	7291.8561	4788.5714	904.49738	2351.4124	6921.4323	3793.6347	1202.9422	**634.22811**	5693.7494	164.11823	1115.3282	35.679722
Avg. Time		261.92	264.49	301.08	255.17	255.45	269.06	308.88	308.94	502.47	150.04	285.80	**239.22**	327.37	245.72	212.02	285.51
Case 8		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	0.87489	1.314177	0.947386	0.867118	0.877342	0.76481	0.930045	0.90522	1.334332	0.967618	0.76900	0.79554	0.738848	0.725267	0.766733	**0.698257**
	FC	77467.27	139558.1	71383.94	64014.34	46283.96	54454.68	48588.33	76080.18	51055.86	59361.3	51174.37	60242.97	52919.11	46328.47	49056.64	**46393.1**
	E	3.531291	8.503072	2.953806	2.457907	1.437213	1.774682	1.451649	3.491641	2.151557	2.018588	2.205882	2.477028	1.742531	1.817771	1.534486	**1.741472**
	P Loss	68.71333	185.8973	60.32383	54.09544	22.78219	42.02103	25.12552	84.50794	40.86976	49.66917	37.21704	51.10564	30.39233	39.76151	62.80557	**42.41244**
	VD	0.87489	2.79196	0.947386	1.514162	1.804974	0.775069	0.960903	0.957758	1.541778	2.475228	0.774521	0.888123	0.738889	0.825756	1.132536	**0.730941**
	L-index	0.366155	0.431231	0.381752	0.374121	0.378877	0.371269	0.362797	0.375848	0.388543	0.423943	0.366919	0.370958	0.374678	0.371455	0.376177	**0.376513**
Worst		1.06290	1.647234	1.157475	1.007057	1.083967	0.796809	1.072034	1.121556	1.445233	1.105013	0.877273	0.89685	1.018463	0.806681	0.877312	**0.715857**
Mean		0.98140	1.495167	1.014351	0.945841	0.989432	0.78408	1.007912	1.057076	1.39395	1.041196	0.828977	0.836225	0.881658	0.763481	0.818537	**0.705231**
Std.		0.071406	0.127539	0.085375	0.051338	0.084904	0.012927	0.057033	0.086519	0.044439	0.053894	0.040889	0.041289	0.119936	0.032058	0.054105	**0.007561**
Avg. Time		253.22	263.80	301.46	256.54	254.19	268.31	307.18	314.55	500.24	150.00	282.37	237.21	330.31	243.16	211.44	**286.74**
Case 9		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Fit	50702.1	104515.3	51490.8	47186.1	51049.0	47741.6	46117.5	45749.4	69141.6	54120.0	46463.9	45531.2	59311.4	45388.4	45864.1	**45321.2**
	FC	46971.32	126614.7	45794.7	51963.8	45622.36	47196.02	45356.75	45247.1	46723.5	49382.92	46052.38	45111.76	45213.15	45064.27	45757.13	**44928.24**
	E	1.600995	7.338807	1.736301	1.895413	1.456291	1.576782	1.794756	1.679243	1.852101	1.608671	1.433802	1.449611	1.740641	1.39431	1.655189	**1.595312**
	P Loss	25.68659	168.1893	25.80581	31.52395	22.22106	22.54173	22.30179	23.01131	20.30871	26.91048	21.84252	21.15591	25.70948	21.38334	27.93819	**23.29527**
	VD	1.613216	2.836551	1.496675	2.196883	2.046321	1.308957	1.38518	1.270981	2.164107	1.770673	1.237652	1.218376	2.007308	1.641555	1.337391	**1.55910**
	L-index	0.376609	0.449168	0.392765	0.383004	0.366554	0.385463	0.377006	0.36439	0.398163	0.358431	0.373793	0.367032	0.359205	0.373784	0.369776	**0.376258**
Worst		70591.0	176879.6	66496.1	56237.3	53494.9	52791.5	52318.7	52885.5	118956.7	60470.0	54521.4	46106.4	74780.9	46287.0	47287.9	**45546.8**
Mean		58749.2	142622.5	58107.6	50083.1	52632.3	50236.3	47980.0	48352.0	83768.1	58016.4	48463.4	45856.4	69100.5	45509.5	46469.9	**45392.5**
Std.		7487.646	25681.03	6728.882	3573.293	973.627	1920.082	2472.547	2830.778	20266.26	2660.907	3433.926	254.9736	6044.952	208.1156	591.8971	**104.5972**
Avg. Time		251.22	261.48	311.03	256.55	255.45	272.96	302.39	302.86	487.32	150.75	294.89	238.58	326.44	248.84	210.25	**292.84**

Summarization of the IEEE 30 bus system and the lower and upper bounds for the optimization is given in Table 49 (**Appendix**). The 25 different scenarios, the variations in loading and renewable power and the scenario probabilities are given in Table 50 (**Appendix**). The decision variables for the best-performing algorithms for all the 12 scenarios

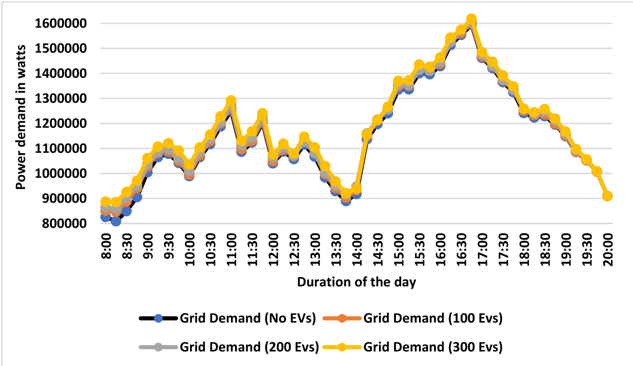

FIGURE 1. Daily load curves with various levels of EV loading at VIT campus.

are given in Table 51 (**Appendix**) followed by the decision variables for the best-performing algorithms for the next 13 scenarios in Table 52 (**Appendix**) respectively.

Optimization of two cases i.e., minimization of real power loss and voltage deviation respectively with 19 decision variables for 25 cases is done through the 16 algorithms. The number of function evaluations has been set to 20,000 and 30 independent runs have been set for all the algorithms. The best results for 25 scenarios have been tabulated in Table 20. In Table 20, P Loss denotes the real power loss in MW, VD denotes the voltage deviation in p.u.

Analysis of Results:

1) ME-SGO had the best performance for 13 out of the 25 scenarios and ISGO had the best performance for 8 cases respectively. The ORPF with uncertain EV loading and renewable power is a complex optimization problem and can be the most demanding on the optimization algorithm. For the same power loss and voltage deviation, there could multiple combinations of decision variables on account of the high non-linearity associated with it.
2) It is necessary for the algorithm to be quickly able to explore the search source to determine the feasible areas and exploit it sufficiently to ensure a better result for all cases. ME-SGO in this regard has been good at covering the various feasible zones and quickly converging to the global best solution. The *learning rate* has been crucial to adapt to these multi-constrained landscapes and prevent an early entrapment.
3) HS-WOA performed poorly for most of the cases as it does not include multiple adaptive strategies and measures to strategically adapt to the complex landscapes.

C. OPTIMAL DYNAMIC CHARGING (ODC)

The third problem in EV optimization is the dynamic optimization strategy of EV charging based on [55] with 3 levels of EV loading. The grid data considered is based on the average loading data of Vellore Institute of technology, VIT-Campus, Vellore for a period of over a month depicted

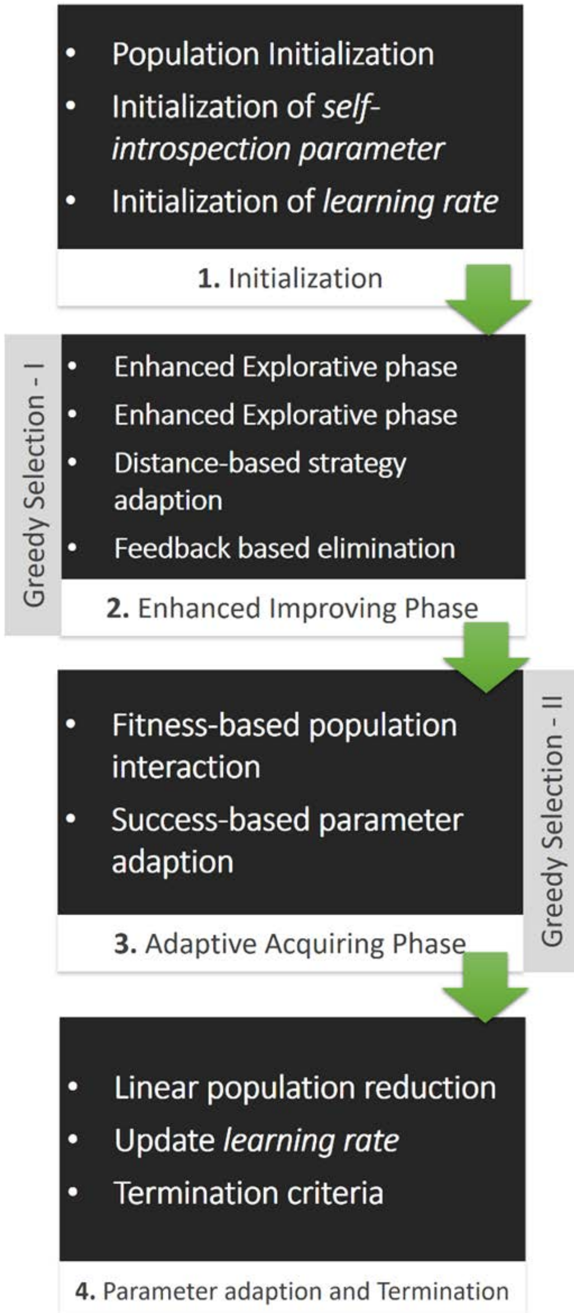

FIGURE 2. Flowchart of ME-SGO.

in Figure 1. The objectives with the current problem are to lower the power curtailment i.e., Minimization of power deviation from the actual load to the ideal load and improve the degree of satisfaction of the EV owners while the constraints include the EV charging power limits, battery and SoC limits, transformer and branch power transmission limits etc. The mathematical model, simulation details and constraints are provided in Table 53 (**Appendix**).

In the current model, 3 cases of EV loading i.e., 100EVs, 200EVs and 300 EVs are considered as the additional load

TABLE 20. Tabulation of the best solutions of ORPD for the IEEE 30-bus system with EV loading for all the algorithms in comparative analysis.

		SGO	ISGO	MSGO	HSWOA	HSWOA+	MEGWO	GABC	CLPSO	EPSO	MPEDE	L-SHADE	GWO	WOA	SMA	ChOA	ME-SGO
S1	PLoss	1.932971	1.929629	2.635937	2.545767	2.910331	2.053861	1.918048	1.912805	1.903143	1.823973	1.807311	1.872238	1.810626	1.834286	2.029472	**1.272131**
	VD	0.198797	0.149998	0.915121	0.796091	0.56602	0.183419	0.112141	0.499419	0.162914	0.181687	0.100303	0.12888	0.172939	0.178485	0.637095	**0.079769**
S2	PLoss	3.034607	2.911068	4.02092	3.261284	3.831528	2.912598	2.939793	5.386464	5.478234	4.98187	5.100201	5.035536	5.03191	13.61675	5.350959	**2.385291**
	VD	0.108001	0.186065	0.891866	0.462253	0.750468	0.177401	0.147563	0.467235	0.436899	0.280665	0.232322	0.290414	0.310049	0.889528	0.481416	**0.10425**
S3	PLoss	4.050435	**4.018547**	5.56512	5.481558	5.215132	3.962584	4.189747	4.45478	4.508071	4.083299	4.16278	4.24444	4.247537	4.197261	4.425146	4.073138
	VD	0.226095	**0.237933**	1.001946	0.854046	0.91595	0.261811	0.203121	0.601284	0.432995	0.304434	0.220081	0.200693	0.218107	0.244802	0.607802	0.300165
S4	PLoss	5.121291	5.005016	7.144435	6.933936	5.776784	5.163818	5.047568	5.515535	5.361118	**5.001507**	5.025104	5.242311	5.151873	7.180748	5.346155	5.008897
	VD	0.287569	0.355815	1.242914	0.999261	0.245351	0.25677	0.303228	0.779034	0.44091	**0.328735**	0.314506	0.237176	0.286075	1.623881	0.659814	0.288696
S5	PLoss	2.286954	2.239111	3.081891	2.973421	2.951506	2.325981	2.325929	2.328858	2.389046	2.244215	2.258494	2.249694	2.248763	2.25476	2.833351	**2.224851**
	VD	0.119634	0.125692	0.772443	0.652224	0.632727	0.171576	0.175292	0.309516	0.081013	0.106733	0.09226	0.140925	0.140738	0.091981	0.506008	**0.098317**
S6	PLoss	3.390527	3.293096	4.539185	4.415615	4.399017	3.25084	3.252435	8.760638	8.670653	7.92667	8.015465	7.984193	7.967401	8.154562	8.642578	**1.447803**
	VD	0.175959	0.140274	0.946991	0.805703	0.618252	0.172625	0.152564	0.638255	0.543061	0.308051	0.311256	0.362066	0.363704	0.274356	0.339196	**0.103240**
S7	PLoss	1.989736	1.983439	2.753536	1.940648	2.560121	1.977352	3.077462	3.242586	3.389104	3.162368	3.003847	3.160032	3.144108	3.0674	3.448322	**1.214170**
	VD	0.134996	0.133103	0.798072	0.429147	0.707025	0.125744	0.265814	0.492368	0.528928	0.280143	0.193155	0.124587	0.136362	0.159601	0.424843	**0.193152**
S8	PLoss	1.141306	**1.090563**	1.601544	1.506319	1.522143	1.65846	1.226584	2.323261	2.346949	2.27332	2.154397	2.2919	2.248363	2.280959	2.343086	1.950551
	VD	0.086546	**0.070346**	0.721633	0.589116	0.539044	0.148342	0.200648	0.439583	0.187689	0.12606	0.260392	0.156464	0.135609	0.107132	0.682068	0.079359
S9	PLoss	3.839295	3.805768	5.426217	5.209118	5.24395	3.805169	4.662669	3.89672	3.781944	3.538782	3.568678	3.70476	3.70494	3.538519	3.94805	**2.360044**
	VD	0.226823	0.324267	1.234898	1.04583	0.742731	0.262616	0.465464	0.537731	0.728631	0.251918	0.215254	0.142626	0.139281	0.270207	0.65813	**0.150974**
S10	PLoss	6.814422	6.560179	9.221888	6.830912	9.101093	6.568557	6.676938	3.192303	3.445345	2.975293	3.044854	3.066962	**3.019415**	4.226896	3.190877	4.316651
	VD	0.228835	0.337514	1.090287	0.423508	1.339842	0.302907	0.282563	0.448578	0.682059	0.186337	0.12894	0.172523	**0.165084**	0.925048	0.569316	0.333765
S11	PLoss	7.285111	7.170113	10.18293	10.09424	8.230743	7.138713	7.434624	2.103569	2.101277	2.03624	2.023726	2.046331	2.008073	2.809689	2.059152	**0.927722**
	VD	0.268623	0.331752	1.25114	1.14634	0.396926	0.361588	0.219448	0.510754	0.095795	0.084278	0.155742	0.120506	0.133489	0.907331	0.448002	**0.048104**
S12	PLoss	1.802195	1.755863	2.475999	2.374096	2.420357	1.734714	1.855751	1.548686	1.525406	1.463571	1.461345	1.504354	1.489039	1.490994	1.680906	**1.174276**
	VD	0.105223	0.118498	0.784828	0.616257	0.728642	0.169616	0.153577	0.495822	0.088003	0.08686	0.093472	0.147833	0.126791	0.145714	0.490055	**0.082227**
S13	PLoss	1.851006	**1.755857**	2.406851	2.246572	2.371681	1.879733	1.796959	4.706261	4.716069	4.357286	4.343612	4.450841	4.441455	6.268629	4.648865	1.781345
	VD	0.121314	**0.086189**	0.638227	0.604262	0.543867	0.193533	0.091846	0.679503	0.502908	0.286516	0.292968	0.264514	0.245298	1.265736	0.499669	0.073202
S14	PLoss	2.656599	**2.469085**	3.473983	3.430008	3.139891	2.464964	2.502635	3.759602	3.529041	3.409013	3.4928	3.595024	3.48801	3.38585	3.569835	2.844847
	VD	0.104897	**0.226025**	0.797188	0.666531	0.395873	0.238173	0.141584	0.471429	1.055427	0.235003	0.152769	0.133578	0.201524	0.287583	0.70434	0.131042
S15	PLoss	0.855361	**0.786201**	1.211928	1.214002	1.216695	0.802893	0.922211	7.244401	7.264662	6.645432	6.633843	6.787607	6.760767	6.658298	7.113343	2.429782
	VD	0.065856	**0.105743**	0.526076	0.494324	0.5743	0.088033	0.379619	0.658685	0.459197	0.409473	0.277644	0.274493	0.37045	0.328217	0.502298	0.099792
S16	PLoss	3.33883	3.212729	4.395847	4.356915	4.272798	3.121005	3.232748	3.227419	3.296063	3.025668	2.964146	3.071703	3.00211	2.998384	3.347443	**1.828701**
	VD	0.155376	0.143366	0.979574	0.903694	0.722348	0.287702	0.113599	0.434201	0.081484	0.173131	0.211939	0.158381	0.204347	0.214506	0.523215	**0.087598**
S17	PLoss	3.107156	3.040167	4.283999	3.116984	3.826696	3.11164	3.426614	2.431957	2.435403	2.367062	2.334645	2.356833	2.316162	3.255189	2.728368	**1.749486**
	VD	0.277889	0.303713	0.925192	1.146546	0.432349	0.175227	0.119076	0.347192	0.185815	0.109249	0.125139	0.151824	0.139186	0.890467	0.550189	**0.088672**
S18	PLoss	4.503983	4.383404	6.17592	6.049884	5.405976	4.495184	4.593919	1.459092	1.427615	1.440354	**1.392526**	1.427021	1.400719	2.080497	1.672819	1.792577
	VD	0.313412	0.365397	0.89148	0.696642	0.606691	0.192799	0.146378	0.465867	0.096833	0.163955	**0.100518**	0.140483	0.142421	1.03589	0.648113	0.12625
S19	PLoss	2.154121	2.059824	2.939623	2.851163	2.884273	2.101232	2.150284	2.159701	2.202006	2.056937	2.095277	2.142969	2.068944	2.930009	2.305237	**1.021149**
	VD	0.108327	0.238906	0.855344	0.714645	0.778489	0.177179	0.136751	0.335823	0.083416	0.135803	0.083819	0.119535	0.105888	0.884103	0.569699	**0.082698**
S20	PLoss	3.827775	3.872621	5.338196	5.333235	4.762114	3.810682	3.867942	2.478729	2.462797	2.382787	2.348174	2.406634	2.289443	3.357834	2.453255	**2.240514**
	VD	0.327862	0.249712	0.902199	0.887312	0.455082	0.313254	0.248009	0.557394	0.284875	0.113053	0.120709	0.124417	0.253808	1.016908	0.646436	**0.087961**
S21	PLoss	0.913847	**0.808554**	1.247455	1.01399	1.142741	0.845886	2.369438	3.962935	3.96641	3.640292	3.81112	3.831252	3.749689	3.698089	3.945832	3.546075
	VD	0.178804	**0.053719**	0.588724	1.339684	0.485596	0.114285	0.202575	0.443355	0.40396	0.332624	0.176232	0.186432	0.319769	0.281261	0.653483	0.213248
S22	PLoss	1.671204	**1.650933**	2.334466	2.29353	2.172087	1.748394	1.642929	2.481381	2.515785	2.414473	2.441825	2.482936	2.439284	2.412195	2.44764	1.882837
	VD	0.154236	**0.126303**	0.909153	0.828443	0.553282	0.147601	0.154896	0.432517	0.193513	0.221046	0.10165	0.143014	0.116392	0.113182	0.582481	0.132173
S23	PLoss	3.529168	3.371869	4.796614	3.461212	5.045929	3.458185	3.472509	1.889181	1.888849	1.834584	1.814342	1.827532	1.796291	**1.779429**	1.894392	2.014286
	VD	0.150612	0.27852	0.873188	1.17193	0.482619	0.185568	0.205268	0.405637	0.089744	0.093478	0.090991	0.138747	0.149605	**0.156463**	0.806631	0.161605
S24	PLoss	1.995408	**1.976460**	2.753628	2.660848	2.558383	1.999088	3.27234	3.131247	3.24859	2.94712	2.896174	3.011492	2.960594	3.041809	3.393585	4.233568
	VD	0.13713	**0.156287**	0.92767	0.759748	0.855368	0.134269	0.136567	0.384725	0.070696	0.125078	0.194749	0.147166	0.161156	0.125712	0.428606	0.422484
S25	PLoss	3.33787	3.206056	4.587765	4.420839	4.509799	3.342147	3.204957	4.022699	4.027331	3.700981	3.918119	3.77492	3.934864	3.724272	4.376438	**2.225839**
	VD	0.242227	0.283588	0.922232	0.630881	0.885908	0.121437	0.271207	0.583483	0.378261	0.261458	0.124275	0.292347	0.285487	0.278223	0.572486	**0.118801**

TABLE 21. Tabulation of the best solutions with statistical analysis of ODC with 100 EVs for all the algorithms in comparative analysis.

Case 1 (100 EVs)		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	**F**	22.71266	22.72253	22.73018	22.74626	22.63343	22.68725	22.63225	22.63153	22.74269	22.63705	22.6834	22.69211	22.64236	22.62973	22.68626	**22.62964**
	P	5.6696E+07	5.6763E+07	5.6782E+07	5.6791E+07	5.6516E+07	5.6675E+07	5.6526E+07	5.6524E+07	5.6767E+07	5.6516E+07	5.6665E+07	5.6677E+07	5.6546E+07	5.6531E+07	5.6658E+07	**5.6526E+07**
	EVc	86	85	86	86	85	85	86	86	87	85	86	85	86	86	86	**86**
Mean	**F**	22.7127	22.7440	22.7489	22.7463	22.6378	22.6976	22.6333	22.6355	22.7455	22.6372	22.6912	22.6956	22.6450	22.6389	22.6914	**22.6363**
	P	5.6717E+07	5.6811E+07	5.6829E+07	5.6805E+07	5.6535E+07	5.6687E+07	5.6536E+07	5.6539E+07	5.6808E+07	5.6541E+07	5.6685E+07	5.6693E+07	5.6560E+07	5.6549E+07	5.6681E+07	**5.6537E+07**
	EVc	85	84	84	84	84	83	84	84	85	84	85	84	85	84	85	**85**
Worst	**F**	22.7127	22.7562	22.7678	22.7463	22.6407	22.7020	22.6340	22.6382	22.7478	22.6376	22.7002	22.7091	22.6458	22.6446	22.7038	**22.6407**
	P	5.6738E+07	5.6847E+07	5.6876E+07	5.6822E+07	5.6558E+07	5.6711E+07	5.6542E+07	5.6552E+07	5.6826E+07	5.6551E+07	5.6707E+07	5.6729E+07	5.6571E+07	5.6568E+07	5.6716E+07	**5.6558E+07**
	EVc	84	83	81	83	83	82	83	81	83	83	84	83	84	82	84	**82**
Std.	**F**	2.46E-05	1.40E-02	1.42E-02	3.18E-05	3.95E-03	6.56E-03	9.36E-04	3.58E-03	2.61E-03	2.18E-04	7.33E-03	7.56E-03	1.46E-03	7.77E-03	7.77E-03	**6.01E-03**
	P	1.8940E+04	3.0789E+04	3.5267E+04	1.2233E+04	1.6105E+04	1.5757E+04	6.6354E+03	1.0173E+04	2.3772E+04	1.4479E+04	1.8330E+04	2.0673E+04	1.1333E+04	1.6813E+04	2.3746E+04	**1.3400E+04**
Avg. Time		260.231343	253.736602	247.207147	292.273444	269.194838	277.414758	291.296135	302.36924	351.428327	281.693554	288.754031	275.790107	288.137164	298.989763	251.379349	**298.786541**

and are set to arrive at the campus during any period of the day with the morning times being the most crowded. It is assumed that each EV requires 6kW of charging power from the grid. The optimization of the power demand for every 15 minutes starting from 08:00 Hrs. to 20:00 Hrs. is performed and it is assumed that the EV's have a battery level randomly distributed between 0.1 and 0.9 with randomized charging times.

For the three cases considered, 20,000 Function evaluations have been set with all the 16 algorithms given 30 independent runs. The tabulation of the best solutions with statistical analysis and computational times of ODC with 100 EVs, 200 EVs and 300 EVs for all the algorithms in the comparative analysis are given in Table 21, Table 22 and Table 23 respectively. The notations F, P, EVc stand for the fitness value, power curtailment minimized and the number of EVs fully charged.

Analysis of Results:

1) Case 1 with 100 EVs had ME-SGO followed by MPEDE deliver the best performance in terms of minimization of the total cost function and a higher degree of satisfaction among the EV owners. ChOA on the other hand recorded the highest number of EVs fully charged although the cost function was higher compared to that of ME-SGO and MPEDE.
2) L-SHADE dominated case 2 with the best cost function and highest number of EVs fully charged. Although ME-SGO had the least power curtailment, the DoS was lower compared to the other algorithms.
3) In case 3, a competitive performance was noted between ME-SGO and EPSO with ME-SGO outperforming EPSO by a small margin.
4) All three cases recorded a competitive performance with the 16 competitive algorithms with the

TABLE 22. Tabulation of the best solutions with statistical analysis of ODC with 200 EVs for all the algorithms in comparative analysis.

Case 2 (200 EVs)		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	F	22.7804	22.8668	22.9940	22.9839	22.7559	22.8798	22.9494	22.7674	22.8476	22.8721	**22.7415**	22.7545	22.7353	22.7511	22.8711	22.7545
	P	5.6864E+07	5.7085E+07	5.7418E+07	5.7317E+07	5.6831E+07	5.7079E+07	5.7332E+07	5.6782E+07	5.7078E+07	5.7043E+07	**5.6810E+07**	5.6771E+07	5.6797E+07	5.6810E+07	5.7137E+07	5.6755E+07
	EVc	137	142	138	143	147	140	145	141	143	138	**145**	142	145	142	143	136
Mean	F	22.8480	22.8924	23.0335	23.0323	22.7862	22.8835	23.0261	22.7744	22.8821	22.9001	**22.7653**	22.7606	22.7782	22.7671	22.9045	22.7626
	P	5.6971E+07	5.7156E+07	5.7498E+07	5.7456E+07	5.6894E+07	5.7136E+07	5.7459E+07	5.6846E+07	5.7164E+07	5.7134E+07	**5.6844E+07**	5.6834E+07	5.6866E+07	5.6863E+07	5.7183E+07	5.6809E+07
	EVc	136	141	137	141	145	139	143	138	142	137	**143**	140	144	141	142	134
Worst	F	22.8649	22.9129	23.0598	23.0444	22.8010	22.8860	23.0453	22.7761	22.9186	22.9072	**22.7713**	22.7622	22.7895	22.7799	22.9129	22.7680
	P	5.7121E+07	5.7241E+07	5.7608E+07	5.7570E+07	5.6962E+07	5.7174E+07	5.7572E+07	5.6899E+07	5.7256E+07	5.7227E+07	**5.6887E+07**	5.6864E+07	5.6933E+07	5.6909E+07	5.7241E+07	5.6879E+07
	EVc	134	139	135	139	143	139	141	137	140	135	**142**	138	143	140	141	133
Std.	F	3.78E-02	2.37E-02	3.60E-02	2.70E-02	2.11E-02	3.42E-03	4.29E-02	3.87E-03	2.60E-02	1.57E-02	**1.33E-02**	3.43E-03	2.40E-02	1.03E-02	1.87E-02	7.36E-03
	P	9.8529E+04	6.8260E+04	7.4413E+04	9.4863E+04	5.6441E+04	3.8934E+04	8.9910E+04	4.5660E+04	6.5127E+04	6.5180E+04	**3.2515E+04**	3.7025E+04	6.1870E+04	3.9018E+04	4.2540E+04	5.4129E+04
Avg. Time		468.489404	456.797049	445.042199	526.174173	484.626209	499.424371	524.414743	544.349437	632.669553	507.127403	**519.838242**	496.499543	518.727709	538.265431	452.553332	537.899574

TABLE 23. Tabulation of the best solutions with statistical analysis of ODC with 200 EVs for all the algorithms in comparative analysis.

Case 3 (300 EVs)		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	F	23.0469	23.2846	23.2073	23.1350	23.1442	23.2249	23.1963	23.2107	23.2169	23.1294	22.9856	23.2128	23.0051	23.0778	23.1299	**23.0017**
	P	5.7412E+07	5.7635E+07	5.7842E+07	5.7794E+07	5.7765E+07	5.7734E+07	5.7646E+07	5.7650E+07	5.7864E+07	5.7774E+07	5.7324E+07	5.7878E+07	5.7268E+07	5.7644E+07	5.7765E+07	**5.7373E+07**
	EVc	201	196	197	192	191	201	200	196	195	195	196	196	192	191	199	**194**
Mean	F	23.0615	23.2914	23.2324	23.1968	23.1834	23.2613	23.2194	23.2165	23.2243	23.1938	22.9950	23.2295	23.0328	23.1685	23.1615	**23.0088**
	P	5.7509E+07	5.7944E+07	5.7961E+07	5.7901E+07	5.7883E+07	5.7958E+07	5.7854E+07	5.7869E+07	5.7955E+07	5.7906E+07	5.7400E+07	5.7960E+07	5.7440E+07	5.7873E+07	5.7825E+07	**5.7448E+07**
	EVc	189	187	185	185	178	188	186	177	185	183	187	190	184	185	189	**184**
Worst	F	23.0690	23.2986	23.3127	23.2326	23.2198	23.2778	23.2267	23.2241	23.2393	23.2287	23.0002	23.2376	23.0662	23.2071	23.2088	**23.0161**
	P	5.7594E+07	5.8170E+07	5.8226E+07	5.8019E+07	5.7976E+07	5.8120E+07	5.8006E+07	5.8001E+07	5.8030E+07	5.8006E+07	5.7441E+07	5.8017E+07	5.7589E+07	5.7970E+07	5.7958E+07	**5.7493E+07**
	EVc	175	173	169	175	172	171	176	170	175	176	180	181	172	179	174	**175**
Std.	F	9.11E-03	6.16E-03	4.51E-02	4.40E-02	3.64E-02	2.09E-02	1.31E-02	5.63E-03	9.15E-03	4.63E-02	5.82E-03	9.73E-03	2.96E-02	5.41E-02	4.10E-02	**6.38E-03**
	P	7.1508E+04	1.9467E+05	1.5613E+05	9.4638E+04	8.9525E+04	1.7338E+05	1.5176E+05	1.4974E+05	6.3392E+04	1.0479E+05	4.7463E+04	6.0164E+04	1.1887E+05	1.3690E+05	8.2845E+04	**4.4964E+04**
Avg. Time		613.037566	597.737640	582.355937	688.520447	634.153236	653.517236	686.218161	712.303525	827.874013	663.596970	680.229623	649.689979	678.776444	704.342353	592.184563	**703.863615**

TABLE 24. Tabulation of the best solutions with statistical analysis of EEC with UDDS for all the algorithms in comparative analysis.

Case 1 SOC 0.7		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Cu Co	3442.525	5639.155	4153.224	5176.26	3761.032	5523.486	5425.31	7198.863	6755.925	5641.464	2876.074	3677.406	5810.096	3008.699	15580.74	**2756.489**
	Pb	1678880.6	1545947	1761028	1673392	1654236	1786455	1675401	1508944	1673079	1496516	2872.003	1702139	1345327	576358	1061028	**580095.9**
	SOC_{mean}	0.496736	0.501626	0.504167	0.502739	0.500576	0.50374	0.505122	0.506303	0.505432	0.500084	2714.078	0.505445	0.503117	0.506047	0.501449	**0.501504**
	PE - Pb	9839.4	18375.32	380.3415	69085.62	10722.9	150982.7	428819.1	16440.95	167371.5	1313647	2705.405	366372.5	1250163	515350	489240.6	**526226.6**
	Pe	681838.0	859496.5	717813.6	709993.7	607453	729005.5	918174.3	989807.2	577799.9	839615.8	2696.32	583930	1000716	545535.9	2640725	**491890.2**
Mean	Cu Co	3516.849	5760.303	4384.09	5405.873	4006.595	5655.621	5840.964	7613.794	7033.568	5873.237	2876.074	3885.288	6399.647	3028.313	16107.17	**2827.506**
	Pb	1650463.3	1527161	1739740	1621572	1576808	1735012	1619860	1426643	1441333	1381085	2872.003	1666237	1540192	541955.8	274403	**565657.2**
	SOC_{mean}	0.499021	0.499099	0.497913	0.50046	0.498973	0.501022	0.503755	0.501093	0.499965	0.496584	2714.078	0.499454	0.50177	0.501962	0.49749	**0.498569**
	PE - Pb	12250.2	17791.84	4209.437	82911.77	6319.97	174970.2	472634.1	21613.47	278232.9	1440710	2705.405	394135.4	1139287	506507.4	58702.81	**510793.5**
	Pe	612666.1	889592	775348.7	751485.9	680482.6	769316.9	994207	1092275	809545.8	987742	2696.32	628097.2	1111592	554791.9	2824878	**516834.6**
Worst		3591.405	5965.865	4503.475	5614.856	4324.434	5896.957	6018.182	8117.021	7603.128	6140.331	3061.564	4276.021	6953.713	3061.564	16575.81	**2934.736**
Std.		70.234226	134.3455	149.6847	194.2422	249.1214	144.7148	241.8929	351.6697	336.3761	180.2292	20.44363	229.8677	467.202	20.44363	381.9342	**80.92142**
Avg. Time		0.00033	0.001224	0.00085	0.000999	0.001142	0.00067	0.000657	0.001936	0.001108	0.00073	0.00043	0.001298	0.001721	0.00043	0.001194	**0.000393**
Total Time		0.45229	1.177038	1.164022	1.368562	1.564219	0.917503	0.900262	2.652742	1.517435	1.000124	0.588902	1.777696	2.357968	0.588902	1.636053	**0.53874**
Case 2 SOC 0.5		**SGO**	**MSGO**	**ISGO**	**HS-WOA**	**HS-WOA+**	**GWO**	**WOA**	**SMA**	**ChOA**	**CLPSO**	**L-SHADE**	**GABC**	**EPSO**	**MPEDE**	**MEGWO**	**ME-SGO**
Best	Cu Co	3084.823	4746.878	3630.526	4464.598	3865.89	3501.828	3292.931	5369.004	6409.183	5000.185	**2624.962**	3446.037	3835.611	2724.672	15578.55	2678.178
	Pb	1654452.3	1391383	1703776	1540885	1610089	1521874	1332705	1261072	1474082	1312674	**554650.2**	1678337	1726962	499698.7	816033.7	571134.2
	SOC_{mean}	0.399981	0.403115	0.403816	0.400476	0.401368	0.40106	0.40131	0.401381	0.401425	0.400662	**0.402718**	0.401108	0.403095	0.402222	0.399549	0.404408
	PE - Pb	9962.0	15151.88	1175.759	35560.94	12410	44002.93	132698.6	784.8351	267207.3	1262520	**522682.9**	332366.6	1014608	532193.3	372852.8	538114.7
	Pe	606388.8	704932.2	572112.5	594922	651470.7	464423.7	575478	741935.4	776796.8	754363	**490862.1**	548740.2	523917.1	492633.1	2654024	488215.8
Mean	Cu Co	3174.856	4856.287	3789.49	4599.467	4116.336	3716.807	3711.734	5620.88	6682.646	5285.362	**2692.114**	3596.601	3976.717	2763.894	16097.38	2696.872
	Pb	1643811.6	1361287	1609362	1505632	1541966	1481562	1256672	1158604	1414907	1244599	**533617.7**	1629560	1681579	488513.3	930297.5	530756.7
	SOC_{mean}	0.398095	0.401015	0.400453	0.39968	0.398832	0.400376	0.399359	0.399562	0.399659	0.399372	**0.401**	0.399958	0.399057	0.398799	0.340213	0.400613
	PE - Pb	10108.3	16068.87	11567.92	41496.26	7319.619	60551.68	188147.7	1091.634	295253.7	1348574	**516399.1**	374436.4	1047903	513101.5	245148.8	519983.4
	Pe	557175.8	723717.9	653084.7	639660	716323.6	515867.3	631019.1	824236.5	835971.7	888331.4	**495061.9**	589693.2	569300.4	507943.5	2788380	2678.178
Worst		3389.301	4996.988	4060.089	4870.7	4315.961	4235.29	4008.607	5836.233	7034.323	5556.846	**2714.337**	3793.977	4154.702	2815.363	16404.65	2715.276
Std.		124.680526	111.7612	196.8657	165.4908	176.3947	301.5232	291.1801	184.9051	259.075	218.5733	**37.80737**	166.5203	116.99	39.88838	325.6451	14.61866
Avg. Time		0.00033	0.00132	0.000827	0.001096	0.001253	0.000735	0.00069	0.002475	0.001417	0.000933	**0.000550**	0.001659	0.002200	0.000550	0.001527	0.000502
Total Time		0.45230	1.289984	1.126515	1.502052	1.716794	1.006997	0.981985	3.391526	1.940038	1.278657	**0.752910**	2.272781	3.014658	0.752910	2.091691	0.688778

TABLE 25. Tabulation of the best solutions with statistical analysis of EEC with HWFET for all the algorithms in comparative analysis.

Case 1 SOC 0.7		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Cu Co	4006.228	4325.012	4410.168	8200.329	4049.083	4694.555	3908.112	7130.809	6198.935	4382.867	2730.841	4172.73	7196.788	2928.704	9217.388	**2719.115**
	Pb	311879.2	452817.9	303273.4	703384.2	513401.5	555839.3	444020.7	1170626	684600.8	928112.9	559555.9	349759.8	1527797	554626	234367.6	**567082.3**
	SOC_{mean}	0.500876	0.5026	0.50379	0.501522	0.508993	0.506337	0.504193	0.501979	0.50779	0.505899	0.50074	0.508402	0.505066	0.506921	0.500326	**0.501297**
	PE - Pb	510824.2	10735.96	502641	224411.5	248572.9	86399.08	134162.9	10602.96	355192.5	353444.8	524441.9	259971.2	708887	512205.7	968174.6	**510363.8**
	Pe	838084.0	942070.9	829318.8	1598761	801689.2	967452.4	811741.2	1535399	1067626	787151.9	497876.1	731873.2	1148798	539042.7	1794798	**490681.8**
Mean	Cu Co	4101.970	4380.21	4490.181	8434.34	4166.835	5083.413	4122.217	7487.454	6670.77	4443.779	2791.133	4297.78	7241.702	2976.48	9663.46	**2803.447**
	Pb	294580.0	422012.9	294564.5	633220.8	507316	499510.1	371345.3	1107920	611934	955752.1	543413.5	331604.6	1611916	541509.3	158423.4	**552867.3**
	SOC_{mean}	0.498994	0.499046	0.499827	0.497329	0.499512	0.501218	0.50053	0.499948	0.499481	0.502818	0.499459	0.501067	0.501466	0.500923	0.496923	**0.4982**
	PE - Pb	509517.8	12074.97	511273	202743.6	231340.2	89922.3	148238.9	19605.53	366831.1	299313.9	509480.2	221074	647252.4	507144.6	440151.1	**504421.6**
	Pe	819022.2	958810.8	873506.3	1681367	812824.1	1036308	908143.1	1644717	1148732	836111.7	514108.9	753442.7	1184050	549996	1951353	**511510.5**
Worst		4208.105	4441.158	4628.284	8645.64	4261.253	5341.49	4356.555	7710.581	7034.058	4567.718	2869.041	4346.84	7304.331	3034.276	9980.759	**2859.671**
Std.		65.35865	46.66645	85.59708	177.8557	78.58796	237.6411	163.3483	221.3676	331.6452	78.56748	55.08298	72.29783	43.51447	40.48634	279.3467	**59.06853**
Avg. Time		0.000369	0.000616	0.000845	0.000985	0.001143	0.000668	0.00066	0.00196	0.001163	0.00073	0.000406	0.001315	0.001666	0.000412	0.001194	**0.00039**
Total Time		0.281982	0.451151	0.646996	0.754248	0.875257	0.511814	0.505811	1.501245	0.890698	0.559025	0.310805	1.007175	1.275858	0.315877	0.914273	**0.298642**
Case 2 SOC 0.5		**SGO**	**MSGO**	**ISGO**	**HS-WOA**	**HS-WOA+**	**GWO**	**WOA**	**SMA**	**ChOA**	**CLPSO**	**L-SHADE**	**GABC**	**EPSO**	**MPEDE**	**MEGWO**	**ME-SGO**
Best	Cu Co	3803.633	3905.413	4027.966	6174.763	3780.749	3806.089	3698.932	4803.83	4181.746	4199.019	2692.484	4077.571	3734.939	2718.841	9214.903	**2667.734**
	Pb	272103.6	249302.7	295895	415825.8	529646.2	290018.5	382376.2	562936.4	293683.5	856224.6	541873.8	316760.8	753495.7	509960.7	975446.6	**548507.8**
	SOC_{mean}	0.400997	0.401206	0.403992	0.402115	0.403198	0.40171	0.402317	0.402589	0.402396	0.400956	0.402608	0.403465	0.402355	0.401694	0.400726	**0.402887**
	PE - Pb	513308.0	506464.5	502391.8	203463	304430.6	32212.86	102617.5	4404.063	180522.7	292850.2	512839.2	276011.7	212165.4	518333.4	219388.3	**522228.3**
	Pe	767115.7	723132.0	768698.6	1104438	744698.4	782401.2	791862.9	947647.3	720795.1	783350.4	487084.6	699740.3	675007.6	498621.8	1741859	**485733.7**
Mean	Cu Co	3862.653	4241.984	4150.948	6327.431	3884.083	3961.17	3853.209	5070.163	4483.373	4224.506	2717.233	4118.365	3821.522	2764.841	9432.391	**2690.159**
	Pb	267293.5	388154.1	253180.5	396930.3	513065.4	263769.1	315158.6	484230	232509.7	893102.2	532169.1	294563	773848.2	493946.4	837661.9	**529708.8**
	SOC_{mean}	0.399669	0.515485	0.400826	0.400548	0.400374	0.39967	0.399148	0.399772	0.400469	0.399086	0.401136	0.401345	0.400683	0.40034	0.37955	**0.401165**
	PE - Pb	512000.6	515434.6	513803.8	125180.6	284850.3	44452.4	119171.9	9985.23	161019	277339	506089.9	254198.6	171088.9	511137.9	156772	**508878.8**
	Pe	754218.4	831512.0	797421.1	1175162	765013.6	800566.9	851956.4	1021028	769307.5	814136.8	499474.3	720278.3	707886.7	506426.4	1823271	**492809.3**
Worst		3905.413	4225.211	4268.02	6463.974	3984.915	4055.931	3968.656	5321.91	4631.96	4241.05	2771.99	4192.682	4015.565	2832.104	9661.591	**2719.504**
Std.		36.89517	71.15616	85.41863	134.054	76.91295	99.38997	103.68	210.2776	182.349	16.93726	31.74047	45.7914	110.7032	42.89745	198.2991	**20.14817**
Avg. Time		0.000353	0.000398	0.000882	0.001928	0.002237	0.001308	0.000687	0.002249	0.001335	0.000838	0.000466	0.001509	0.001912	0.000473	0.00137	0.000448
Total Time		0.270573	0.291652	0.716517	1.476446	1.713322	1.001879	0.616542	1.722848	1.022177	0.641544	0.356684	1.155847	1.464191	0.362505	1.049232	0.342725

multi-population and multi-strategy based adaptive techniques having the overall best performances. The computational times were also similar for most of the algorithms, although ME-SGO 's computational times were marginally higher for case 3 due to the high dimensionality of the current problem.

TABLE 26. Tabulation of the best solutions with statistical analysis of EEC with FTP-75 for all the algorithms in comparative analysis.

Case 1 SOC 0.7		SGO	MSGO	ISGO	HS-WOA	HS-WOA+	GWO	WOA	SMA	ChOA	CLPSO	L-SHADE	GABC	EPSO	MPEDE	MEGWO	ME-SGO
Best	Cu Co	8214.700	12912.16	8922.819	9336.732	8631.937	11265.76	9849.948	8589.473	13525.42	9381.196	**5954.676**	8893.741	10511.8	6272.151	21974.15	5976.296
	Pb	4737449.7	3625024	4930998	1509195	1495691	2394273	2317673	1912419	2323028	2060590	**1492379**	254373.2	2338715	1502731	2583103	371339.5
	SOC_{mean}	0.499367	0.504128	0.503128	0.50183	0.506335	0.503157	0.500862	0.500706	0.503646	0.502041	**0.503653**	0.503696	0.503615	0.502851	0.503631	0.505104
	PE - Pb	1486908.6	0	1465563	193565.1	264108.8	391062.1	621322.1	852.73	627554.6	1577598	**1497890**	1015357	1769906	306106.9	1172049	307009.6
	Pe	1752568.3	2865391	1672493	1538757	1609405	2106173	2047180	1777671	2147162	1953850	**1145745**	1591473	2159186	1167014	3964837	1157606
Mean	Cu Co	8362.601	13445.42	8981.421	9455.957	8806.87	11913.99	10300.02	8835.263	13704.64	9536.581	**5981.106**	9064.265	10761.12	6300.725	22544.48	5991.907
	Pb	4830448.2	3514974	4891328	1489599	1484928	2239152	2164661	1852773	2231672	2032301	**1241878**	191520.5	2251067	1495462	2064671	344676.4
	SOC_{mean}	0.501255	0.501765	0.499834	0.499084	0.502118	0.501396	0.498767	0.49975	0.50062	0.4998	**0.458982**	0.501318	0.498881	0.499991	0.498736	0.501246
	PE - Pb	1476720.8	0.038285	1484012	147873.8	208435.5	423757.2	668383.4	2924.946	670225.5	1590941	**780377.6**	971930.4	1814423	280449.7	458858.3	293005.3
	Pe	1659196.4	2975038	1702432	1598828	1657202	2216021	2149353	1829642	2208541	2009170	**1157416**	1639552	2227936	1176520	4266666	1162267
Worst		8575.122	13630.67	9088.576	9581.39	8912.814	12446.63	10860.29	9005.71	14195.28	9655.499	**6019.878**	9460.763	11225.48	6364.517	23088.62	6040.27
Std.		152.33470	301.0112	64.64157	87.40027	126.3131	538.3169	381.5202	178.9859	279.3613	100.8436	**23.76907**	233.1718	280.4066	37.83896	471.3631	27.15613
Avg. Time		0.00035	0.001171	0.000574	0.001019	0.001162	0.000655	0.000656	0.001943	0.001115	0.000722	**0.000425**	0.001328	0.001718	0.000413	0.001194	0.00039
Total Time		0.65138	1.594904	1.076278	1.909868	2.177909	1.2283	1.229215	3.642292	2.0909	1.354426	**0.77475**	2.489795	3.220497	0.775002	2.238063	0.731128
Case 2 SOC 0.5		**SGO**	**MSGO**	**ISGO**	**HS-WOA**	**HS-WOA+**	**GWO**	**WOA**	**SMA**	**ChOA**	**CLPSO**	**L-SHADE**	**GABC**	**EPSO**	**MPEDE**	**MEGWO**	**ME-SGO**
Best	Cu Co	7698.288	9129.112	8279.462	6881.158	6456.447	8774.891	7902.885	7326.538	8116.494	6933.825	**5676.965**	7441.224	7629.663	6017.444	14207.05	5931.023
	Pb	4899507.5	4387955	4928457	1423209	1481083	1798818	1774848	1618144	1520121	1550878	**1491915**	130690.9	1676057	1496268	3987899	1492045
	SOC_{mean}	0.400703	0.401731	0.401917	0.4012	0.401373	0.402512	0.401054	0.40039	0.401545	0.401757	**0.500617**	0.400915	0.402597	0.401075	0.401037	0.401398
	PE - Pb	1471863.7	0	1479325	244035.1	223489.2	153826.5	293964.4	803.0337	157250.7	1013007	**1458560**	1300572	1087647	324304.2	2645844	1543698
	Pe	1589969.6	2101074	1571620	1222859	1241451	1675752	1699035	1529224	1448910	1492909	**1151724**	1363817	1592277	1154089	2228897	1149228
Mean	Cu Co	8017.368	9239.633	8341.271	7191.782	6645.568	8922.681	7978.001	7469.404	8203.492	7166.306	**5850.003**	7606.208	7783.056	6045.452	14651.42	5964.841
	Pb	4875667.5	4360876	4912627	1413398	1471753	1750408	1754079	1571049	1485303	1536350	**1245990**	87341.32	1639481	1480101	3860693	1482047
	SOC_{mean}	0.399770	0.399614	0.399717	0.400248	0.399777	0.400723	0.399573	0.399519	0.399907	0.399935	**0.420134**	0.400354	0.400053	0.399491	0.400355	0.400706
	PE - Pb	1483853.2	633.108	1487210	170424	192150.6	174695.6	326785.1	1414.057	167083.8	1090511	**533704.6**	1238371	1166515	304421.3	2545201	1512779
	Pe	1553860.0	2128153	1591932	1301908	1269646	1727277	1730948	1547918	1462172	1513219	**1162104**	1388732	1616350	1167910	2324797	1154385
Worst		8191.978	9350.197	8433.808	7371.896	6778.176	9200.845	8125.522	7583.555	8343.064	7320.165	**5985.923**	7705.515	8034.036	6067.737	14933	5988.283
Std.		232.68091	88.68591	58.06853	188.2746	121.4073	161.9627	91.61926	109.6031	92.31207	156.9984	**150.0233**	98.86344	169.8732	21.2034	287.9228	24.13439
Avg. Time		0.00034	0.001329	0.000599	0.001998	0.002278	0.001284	0.000682	0.003783	0.002171	0.001406	**0.000828**	0.002586	0.003345	0.000804	0.002325	0.000759
Total Time		0.64260	1.498418	1.219651	2.744473	4.269993	2.408196	1.398495	3.092151	4.071331	2.637294	**1.508568**	2.848047	4.270845	1.509058	3.357882	1.423628

TABLE 27. Tabulation of the most cited publications on multi-strategy and multi-population ensemble-based advanced meta-heuristics from the literature.

S. No	Authors and Year	Name	Formulation	Benchmarking	Real-World Application	Improvements
01.	J.K. Cochran et al. in 2003 [6]	MPGA	Two-stage subpopulation evolution with elitism	N/A	Multi-objective scheduling problems for parallel machines with 2 and 3 objectives	MPGA outperformed MOGA in terms of optimality
02.	Zhao et al. in 2005 [9]	MAPSO	Lattice-based agent-agent knowledge sharing and evolution	N/A	Optimal reactive power dispatch for IEEE 30 and 118-bus systems with penalty function approach	Improved optimality with lower execution times
03.	A. Auger et al. [17]	IPOP-CMA-ES	Population size increment technique for every restart	CEC2005 for 10, 20 and 50 dimensions	N/A	Higher optimality for 29 out of 60 cases against local restart strategy.
04.	W. Du et al. in 2008 [10]	MEPSO	Two-part Gaussian local search and differential mutation schemes	2 Multi-modal functions with multiple case studies	N/A	Robust performance of MEPSO with varying dimensionality and function peaks was observed.
05.	Y. Wang et al. in 2011 [11]	SLPSO	Four PSO strategies with self-adaptive learning	26 numerical optimization problems (unimodality, multi-modality, rotation, ill-condition, mis-scale and noise)	economic load dispatch (ELD) with a scaled 10-160 generator problem with both valve points and multiple fuels	Robust performance in terms of optimality and convergence were noted.
06.	Qu et al. in 2012 [14]	NCDE	Euclidean neighbourhood-based mutation	14 basic multimodal and 15 composite multimodal problems	N/A	Out of the 29 problems, improvements were noted for a majority of them
07.	H. Wang et al. in 2013 [7]	MEABC	Three distinct ABC search strategies are strategically allowed to coexist.	12 standard test functions and CEC2013 sifted and rotated test suite	N/A	MEABC performed competitively throughout the benchmarking process.
08.	H. Wang et al. in 2013 [12]	DNSPSO	Diversity and local search systems with greedy selection.	15 benchmark functions and CEC2005 and CEC2010 test suites	N/A	Performance improvements were noted for the 15 test functions and CEC2005 test suite.
09.	W. Deng et al. in 2016 [8]	MGACACO	GA and ACO based multi-population approach.	N/A	A set of 28 Euclidean sample problems (TSP) with sizes ranging from 29 to 18,512 nodes	Improved optimality, fast convergence was observed with the proposed method.
10.	G. Wu et al. in 2016 [15]	MPEDE	Reward based resource allocation with three mutation strategies and populations.	CEC2005 test suite	N/A	An overall competitive performance of MPEDE was noted.
11.	G. Wu et al. in 2018 [16]	EDEV	Reward based DE strategy adaption.	CEC2005 (50D and 100D) and CEC2014 (30D and 50D) test suites.	N/A	Competitive performance compared to the variants of DE was observed.
12.	W. Deng et al. in 2019 [18]	ICMPACO	Multi-population-based co-evolution	N/A	TSP with eight instances and 20 gate assignment problems have been utilized.	ICMPACO proved effective with better optimal results with higher computational times.
13.	H. Chen et al. in 2020 [19]	CMDHHO	HHO with chaos theory followed by the DE mechanism	CEC2017 (50D)	CEC2011 (8 real world issues)	Competitive performance was observed throughout the benchmarking.
14.	M. Wang et al. in 2020 [20]	CMWOA	Combination of chaotic and multi-swarm approaches	N/A	Breast cancer, diabetes, and erythemato-squamous data sets were used	Superior classification performance with the proposed method was obtained.
15.	Y. Guo et al. in 2020 [13]	QPSO_FM	Multi-population and multi-stage perturbation strategies	28 standard benchmark functions	N/A	Competitive performance across most benchmarking functions has been demonstrated.
16.	Q. Tu et al. in 2019 [21]	MEGWO	Enhanced global-best lead strategy and an adaptable cooperative strategy	30 benchmark test problems from the CEC2014 suite	12 feature selection datasets	MEGWO showcased robust optimization results for both benchmarking and feature selection.

D. ENERGY EFFICIENT CONTROL OF PARALLEL HEV

The fourth problem on EV optimization deals with the energy-efficient control (EEC) of a parallel HEV based on [56]. The objective includes the minimization of electricity cost and fuel cost with the maximation of the battery SoC (State of Charge) during the trip duration. The ICE (Internal Combustion Engine) of the PHEV is capable of delivering a maximum power of 30kW and the motor can deliver 15kW with a battery capacity of 5Ah. The mathematical models require the determination of the optimal cumulative cost of operations ICE and EM, optimal battery power, optimal engine power, and the power transferred from the engine to battery to sustain the Soc with constraints on battery power consumption, engine power limits are modelled. The mathematical model, simulation details and constraints are provided in Table 54 (**Appendix**).

The optimization is performed for 3 driving cycles namely HWFET, UDDS and FTP 75. Two cases of investigation with the first case having the SoC limits between 0.7 and 0.3 and the second case with the Soc limits between 0.5 and 0.3 are investigated. The optimization is done through all the 16 algorithms with 50 NFEs provided during every time interval for the drive cycle and 30 independent runs have been considered to validate the results. The tabulation of

TABLE 28. A brief literature survey of the various improved and advanced meta-heuristics applied to the optimization of the various EV domains.

S.No	Authors and Year	Problem Description	Optimization Algorithm Used
01.	X. Wu et al. in 2011 [57]	The optimal drivetrain component sizing problem with respect to the driving performance for a PHEV considering Ni-MH and Li-ion batteries over three different all electric range (AER) cases.	Parallel chaos optimization algorithm (PCOA)
02.	Z. Liu et al. in 2011 [58]	The optimal siting and sizing problem of the distribution generators (DGs) in distribution systems considering the intermittencies associated with PHEV charging and discharging schedules, PV and wind power generation and uncertain load demand has been investigated for an IEEE37-node test feeder system.	Monte Carlo simulation-embedded genetic algorithm
03.	J. Zhao et al. in 2012 [59]	The economic dispatch model accounting for the uncertainties with the PHEV loading and wind power generation (Rayleigh distribution) based on a simulation study to derive the PHEV charging/discharging behaviour is investigated for an IEEE 118-bus system.	Enhanced PSO
04.	J.P. Trovão et al. in 2013 [60]	The multi-level energy management system for a multi-source electric vehicle (battery and super-capacitor powered) with a strategic rule-based restriction of search space to optimize the energy and power sharing is tackled.	Simulated Annealing (SA)
05.	J. Zheng et al. in 2013 [61]	The optimal large scale EV charging strategy considering an aggregation charging model to lower the power fluctuation levels due to EV loading while tracking the variations in the EV charging characteristics is developed.	Standard GA
06.	J. Shen et al. in 2014 [62]	The problem of the optimal sizing (size, volume and cost) of a hybrid energy storage system (HESS) with battery/ultracapacitor (UC) and extend the battery cycle life for EV applications is considered.	DIviding RECTangles (DIRECT) algorithm
07.	J. Tan et al. in 2014 [63]	The optimal integration of PHEVs into the residential distribution grid through a fuzzy logic based stochastic driving pattern model followed by a load profile modelling framework to improve the power quality and lower various cost associated with is proposed.	Two-layer evolution strategy PSO (ESPSO) algorithm
08.	D. Goeke et al. in 2015 [64]	The optimal routing of a mixed fleet of commercial EVs and non EV's utilizing a realistic energy consumption model including the speed, gradient and cargo load distribution to maximize the driving range and lower recharging times is tackled.	Adaptive Large Neighbourhood Search (ALNS) algorithm
09.	H. Yang et al. in 2015 [65]	The EV route optimization with the time-of-use electricity pricing for fast-charging and regular-charging to lower the total distribution costs of the EV route with respect to the constraints on charging, battery use and capacity, electricity pricing, charging constraints etc. is investigated.	Learnable partheno-genetic algorithm
10.	M. Keskin et al. in 2016 [66]	The EV routing problem with time windows with a practical partial recharge strategies with mechanisms for removal of stations and insertion of stations with respect to the charging amount based on the recharging decisions is proposed to improve the routing decisions.	Adaptive Large Neighbourhood Search (ALNS) algorithm
11.	Q. Kang et al. in 2016 [67]	The centralized charging of EVs considering battery swapping strategy and scheduling with charging prioritization and spot electricity pricing is designed to lower the total charging cost, power losses and voltage deviation of an IEEE 30-bus test system	Hybrid of particle swarm optimization and genetic algorithm (PSO-GA+)
12.	S. Suganya et al. in 2017 [68]	The simultaneous co-ordination of distinct PHEV charging stations for a two-area distribution system with different mobility patterns is chosen for the scheduling of EVs in an IEEE 69-bus radial distribution system.	Modified PSO with a multi-evolutionary phase
13.	A. Awasthi et al. in 2017 [69]	The optimal planning of EV charging stations at the Indian city, Allahabad distribution system to lower the deteriorating effects (voltage profile and power quality) of EV loading on the utility distribution system has been investigated.	Hybrid of GA and improved PSO known as GAIPSO
14.	H. Wu et al. in 2018 [70]	The parking lot (PL) dynamic resource allocation system with EV charging facilities through timeslot scheduling with respect to electricity pricing to lower the cost of EV charging prices through optimal scheduling constrained by the EV's charging rate and the transformer limit of the PL is investigated.	Heuristic fuzzy particle swarm optimization (PHFPSO) algorithm
15.	W. Zhao et al. in 2018 [71]	The parametric optimization of an electric-hydraulic hybrid steering system to improve the EV's energy management system by lowering the energy consumption of the actuators by adaptive intervention while considering the aspects of steering economy, steering road feeling, and steering sensitivity is tackled	shuffled particle swarm optimization algorithm (SPSO
16.	T. Zhu et al. in 2019 [72]	The powertrain parameter optimization design of to improve the driving, performance economy and vehicle performance dynamics for PEVs are simulated through Cruise software.	Chaotic PSO (logistic map) known as CPSO
17.	H. Zhang et al. in 2019 [73]	A large-scale problem of locating EV charging stations with service capacity with service risk factors (service capacity and user anxiety) for optimal planning and reduction of social costs is investigated.	Improved Whale Optimization Algorithm (IWOA)
18.	Y. Li et al. in 2020 [74]	The parameter optimization of gear ratios of two-speed transmission to improve the performance of the drive motor and transmission system with respect to the economy and dynamics of the EV is proposed.	Improved genetic algorithm
19.	C.A. Folkestad et al. in 2020 [75]	The optimal charging and repositioning of EVs in a free-floating carsharing system for an improved distribution of cars to maximize the revenue and customer service while marginally raising the operational costs is investigated.	Hybrid Genetic Search with Adaptive Diversity Control algorithm
20.	Y-H. Jia et al. in 2021 [76]	The capacitated EV routing problem (CEVRP) is implemented in two levels with the first level being the optimal routing based on the demands of customers and the second being charging schedule with respect to the electricity constraint is considered.	A bilevel ant colony optimization algorithm (BACO)

TABLE 29. Detailed description of the variants of SGO from the recent literature.

S.No	Authors and Year	Description of the improved/enhanced/hybridized/modified algorithm	Optimization problem tackled	Outcome
1.	Ash K. Singh et al. in 2021 [33]	A hybrid SGO (HSGO) incorporating a mutation phase to enable continuous improvement in the population through the selection of a subset of features from a member of population and comparing it with the worst person to enhance the population diversity is considered.	The proposed hybrid technique was used on combination with support vector classifier for the COVID-19 infection detection from chest X-Ray images for the Kaggle repository" COVID-19 Radiography Database" with 219 COVID-19 positive images, 1341 normal images, and1345 viral pneumonia images.	The proposed method recorded the highest accuracy at 99.65% compared to 12 other deep learning and bio-inspired algorithms while recording higher precision, sensitivity and *FIS* F1 scores.
2.	K. V. L. Narayana et al. in 2020 [32]	Two hybrid variants benefitting from the synergy of SGO and whale optimization algorithm (HS-WOA and HS-WOA+) to improve the balance of exploration and exploitation with a strong immunity to *the curse of dimensionality* are proposed. HS-WOA was aimed towards improving the convergence behaviour while HS-WOA+ was aimed at enhancing the quality of exploration.	Extensive benchmarking analysis with standard benchmark functions, composition functions, five standard engineering problems and eight cases of a multi-unit production planning problem were considered for the validation of the proposed method.	HS-WOA+ outperformed the parent algorithms and other modern meta-heuristics while HS-WOA had a competitive perforce for the various cases of benchmarking tests.
3.	S. Das et al. in 2020 [77]	A modified SGO (MSGO) incorporating a probabilistic selection between a self-improvement phase with chaotic maps (logistic map, iterative map and tent map) and a position updating phase to ensure a global best oriented search is improved has been proposed.	The design optimization of various civil engineering structures (concrete cantilever beam, 31-member bridge truss, G+3-storey frame, ASCE benchmark structure) for different case studies was investigated.	MSGO had a robust performance compared to SGO, PSO and ALO with the least possible error rates, noise contamination and faster computational times.
4.	A. Naik et al. in 2020 [30]	Modified SGO (MSGO) with a modified acquiring phase incorporating a self-awareness probability factor to improve the learning capabilities of the population while boosting the explorative and exploitative potentials with re-initialization within the lower and upper bounds is proposed.	Benchmarking analysis with 7 unimodal, 6 multi-modal and 10 fixed-dimensional multi-modal test functions with higher number of problem dimensions is conducted and statistically validated. Additionally, MSGO was deployed for the optimal short-term hydrothermal scheduling problem (STHS) (3 cases).	MSGO was compared with 20 modern meta-heuristics and performed competitively and obtained lower values of the cost function for the STHS problem in two out of three cases.
5.	J. Fang et al. in 2018 [27]	An improved SGO (ISGO) with population division in the improving phase and elimination – re-initialization system in the acquiring phase to extend its explorative abilities and avoid local entrapment is developed.	ISGO is deployed for the transformer fault diagnosis model using an optimal hybrid dissolved gas analysis features subset with support vector machine classifier to improve the accuracy of the fault diagnose.	ISGOSVM diagnostic model had higher accuracy of 3% compared to SGO's model and 14% higher accuracy compared to the GA model and recorded the highest fault diagnosing accuracy of 92.86%.
6.	Y. Liu et al. in 2018 [28]	A discrete version of an improved SGO (ISGO) with a historical learning phase to improve the population diversity following the improving and acquiring phases is developed.	ISGO is combined with the cluster head multi-hop routing protocol in WSN for the data transmission in a multi-hop manner to prolong the lifetime of the network is investigated.	Compared to the GA and the basic CECA protocols, ISGO's protocol had higher number of surviving nodes at the end of the lifecycle with lower overall lifecycle energy consumption.

the best solutions with statistical analysis and computational times of EEC with UDDS, HWFET and FTP-75 drive cycles for all the algorithms in the comparative analysis are given in Table 24, Table 25 and Table 26 respectively for both the cases investigated. The notations, Cu Co stands for the cumulative cost, Pb is the total power delivered by the battery in watts, SOC_{mean} is the average state of charge, PE-Pb is the total power transferred from engine to battery in watts, Pe is the total power delivered by the engine in watts.

Analysis of Results:

1) The performance of ME-SGO, MPEDE and L-SHADE has been the best for UDDS with ME-SGO and L-SHADE delivering the best performance for cases 1 and 2 respectively. MPEDE and ME-SGO remained robust with the least standard deviations for cases 1 and 2 respectively.
2) ME-SGO dominated for the HWFET drive cycle with the least cumulative costs incurred for both cases. The performances of MPEDE and L-SHADE were similar

TABLE 30. **Description of the algorithm-specific tuning parameters for all the algorithms used in the comparative analysis.**

<table>
<tr><th>Algorithm</th><th>Tuning / Algorithm-specific Parameters</th><th>Value</th></tr>
<tr><td>SGO</td><td>Self-introspection factor (c)</td><td>Set to 0.2</td></tr>
<tr><td rowspan="4">GABC</td><td>Strategy</td><td>ABC/best/1</td></tr>
<tr><td>Limit</td><td>$0.6 \times SN \times D$
where,
SN stands for population scale and
D is the number of problem dimensions</td></tr>
<tr><td>Φ</td><td>random number in the range [−1,1]</td></tr>
<tr><td>Chaotic iteration (K) with sinusoidal iterator</td><td>300</td></tr>
<tr><td rowspan="4">CLPSO</td><td>Acceleration constants (cc_1 and cc_2)</td><td>Both set to 1.49445</td></tr>
<tr><td>Inertia weight (w)</td><td>$0.9 - [1 \text{ to } NFE_{max}] \times (0.7/ NFE_{max})$</td></tr>
<tr><td>Refreshing gap (m)</td><td>Set to 7</td></tr>
<tr><td>Learning Probability (Pc)</td><td>Particles from 1 to 30 have a Pc value ranging from 0.05 to 0.5 based on
$Pc_i = 0.05 + 0.45 \times \frac{\left[exp\left(\frac{10(i-1)}{ps-1}\right)-1\right]}{(exp(10)-1)}$</td></tr>
<tr><td>EPSO</td><td colspan="2">
<table>
<tr><th>Algorithm</th><th>Inertia Weight (w)</th><th>Constriction Coefficients χ</th><th>Acceleration Coefficients c_1, c_2, c</th><th>Neighbourhood size</th></tr>
<tr><td>Inertia weight PSO</td><td>0.9-0.2</td><td>-</td><td>c_1=2, c_2=2</td><td>-</td></tr>
<tr><td>LIPS</td><td>-</td><td>0.729</td><td>c =2</td><td>3</td></tr>
<tr><td>FDR-PSO</td><td>0.9-0.2</td><td>0.729</td><td>c_1=1, c_2=1, c_3=2</td><td>-</td></tr>
<tr><td>CLPSO</td><td>0.9-0.2</td><td>-</td><td>c =3 – 1.5</td><td>-</td></tr>
<tr><td>OLPSO</td><td>0.9-0.2</td><td>-</td><td>c =2</td><td>-</td></tr>
<tr><td>HPSO-TVAC</td><td>-</td><td>-</td><td>c_1=2.5 – 0.5, c_2= 0.5 – 2.5</td><td>-</td></tr>
<tr><td>sHPSO</td><td>0.72</td><td>-</td><td>c_1=2.5 – 0.5, c_2= 0.5 – 2.5</td><td>-</td></tr>
<tr><td>CLPSO with gbest</td><td>0.9-0.2</td><td>-</td><td>c_1=2.5 – 0.5, c_2= 0.5 – 2.5</td><td>-</td></tr>
</table>
</td></tr>
<tr><td rowspan="4">L-SHADE</td><td>Arc rate (r^{arc})</td><td>Set to 2.6</td></tr>
<tr><td>p_{best} rate (p)</td><td>Set to 0.11</td></tr>
<tr><td>Memory size (H)</td><td>Set to 6</td></tr>
<tr><td>$r^{N^{init}}$</td><td>Set to 18</td></tr>
<tr><td rowspan="4">MPEDE</td><td>Ratio (λ_1)</td><td>Set to 0.2</td></tr>
<tr><td>Generation gap (ng)</td><td>Set to 20</td></tr>
<tr><td>Initial crossover rate (μCR)</td><td>Set to 0.5</td></tr>
<tr><td>Initial value of scaling factor (μF)</td><td>Set to 0.5</td></tr>
<tr><td rowspan="2">MSGO</td><td>Self-introspection factor (c)</td><td>Set to 0.2</td></tr>
<tr><td>Self-Awareness probability (SAP)</td><td>Set to 0.7</td></tr>
<tr><td rowspan="2">HS-WOA,
HS-WOA+</td><td>Social interaction factor (s)</td><td>Adaptive (0.8 to 1)</td></tr>
<tr><td>Count</td><td>20 iterations</td></tr>
<tr><td rowspan="2">ISGO</td><td>Self-introspection coefficient (μ)</td><td>Set to 0.2 where (μ–$U(0, 1)$), ‘U’ stands for uniform distribution</td></tr>
<tr><td>λ</td><td>random number in 0 and 1 ($0 < \lambda < 1$)</td></tr>
<tr><td rowspan="3">SMA</td><td>$\overrightarrow{vc}$ (Linear control parameter)</td><td>Decreases linearly from one to zero.</td></tr>
<tr><td>$\overrightarrow{vb}$ (Oscillation control parameter)</td><td>Oscillates randomly between $[-a, a]$ and tends to zero eventually where a is set based on the iteration count.</td></tr>
<tr><td>Control Vector (a)</td><td>$a = arctanh\left[-\left(\frac{t}{T}\right)+1\right]$</td></tr>
<tr><td>GWO</td><td>Control Vector ($\vec{a}$) to balance exploration and exploitation phases</td><td>Follows a linearly decrementing nature from an initial value of 2 to a final value of 0 over the progression of iterations.</td></tr>
<tr><td rowspan="2">WOA</td><td>Control Vector ($\vec{a}$) to balance exploration and exploitation phases</td><td>Linearly decreased from 2 to 0 over the course of iterations</td></tr>
<tr><td>Coefficient Vector ($\vec{A}$)</td><td>Randomized in the interval [-1, 1]</td></tr>
<tr><td rowspan="2">ChOA</td><td>Chaotic Vector (m)</td><td>Tent chaotic map</td></tr>
<tr><td>Control Vector (f)</td><td>Reduced non-linearly from 2.5 to 0 through the iteration process</td></tr>
<tr><td rowspan="2"></td><td>Scale factor (ρ)</td><td>Set between 0.5 and 0.1^2 based on $\rho \sim N(0.5, 0.1^2)$</td></tr>
<tr><td>Global-best guidance rate (GR)</td><td>Set to 0.8</td></tr>
</table>

TABLE 30. *(Continued.)* **Description of the algorithm-specific tuning parameters for all the algorithms used in the comparative analysis.**

MEGWO	Dispersion rate (DR)	DR_{max} = 0.4, DR_{min} = 0
	SR	SR_{max} = 1, SR_{min} = 0.6
	Control Vector ($\vec{a}$) to balance exploration and exploitation phases	Follows a linearly decrementing nature from an initial value of 2 to a final value of 0 over the progression of iterations.
ME-SGO	Initial value of the self-introspsection factor (C_{int})	0.2
	Learning rate (*rate*)	10

TABLE 31. **Description of the 10 CEC2019 benchmark functions (composition functions) used to determine the algorithms' ability to avoid local entrapment.**

Function No.	Function	$F_i^*=F_i(X^*)$	Dimensions	Search Range	Properties
F1	Storn's Chebyshev Polynomial Fitting Problem	1	9	[-8192, 8192]	• Multimodal with one global minimum • Very highly conditioned • Non-separable; fully parameter-dependent
F2	Inverse Hilbert Matrix Problem	1	16	[-16384, 16384]	• Multi-modal with one global minimum • Highly conditioned • Non-separable; fully parameter-dependent
F3	Lennard-Jones Minimum Energy Cluster Problem	1	18	[-4,4]	• Multi-modal with one global minimum • Non-separable; fully parameter-dependent
F4	Shifted and Rotated Rastrigin's Function	1	10	[-100,100]	• Multi-modal • Non-separable • Local optima's number is huge and the penultimate optimum is far from the global optimum.
F5	Shifted and Rotated Griewank's Function	1	10	[-100,100]	• Multi-modal • Non-separable
F6	Shifted and Rotated Weierstrass Function	1	10	[-100,100]	• Multi-modal • Non-separable • Local optima's number is huge
F7	Shifted and Rotated Schwefel's Function	1	10	[-100,100]	• Multi-modal • Non-separable • Local optima's number is huge
F8	Shifted and Rotated Expanded Schaffer's F6 Function	1	10	[-100,100]	• Multi-modal • Non-separable • Local optima's number is huge
F9	Shifted and Rotated Happy Cat Function	1	10	[-100,100]	• Multi-modal • Non-Separable
F10	Shifted and Rotated Ackley Function	1	10	[-100,100]	• Multi-modal • Non-Separable

TABLE 32. **The optimization model for the pressure vessel design.**

F.	Objective Function and Constraints	Range of decision variables
SE1	Pressure Vessel Design Minimize $O(\vec{X}) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.161x_1^2x_4 + 19.84x_1^2x_3$ Subject to the constraints $c_1(\vec{X}) = -x_1 + 0.0193x_3 \leq 0$ $c_2(\vec{X}) = -x_3 + 0.00954x_3 \leq 0$ $c_3(\vec{X}) = -\pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1{,}296{,}000 \leq 0$ $c_4(\vec{X}) = x_1 - x_4 \leq 0$	$0 \leq x_1 \leq 99$ $0 \leq x_2 \leq 99$ $10 \leq x_3 \leq 200$ $10 \leq x_4 \leq 200$
Description: The pressure vessel design requires the optimization (minimization) of the cost through four decision variables to be optimized. The four decision variables (x_1, x_2, x_3 and x_4) include the length of the cylindrical section, the thickness of the head, the inner radius and the thickness of the shell within specified lower and upper bounds. Four inequality constraints with respect to three decision variables (x_1, x_3 and x_4) are present.		

with MPEDE being consistent at delivering results with lower deviation. It is evident that adaptive and multi-strategy adoption by the three of these algorithms has resulted in better overall performance.

3) FTP-75 witnessed L-SHADE followed by ME-SGO delivering the best performances with ME-SGO falling behind L-SHADE. The reason for L-SHADE being the top performer is due to its maintenance of historical memory of a diverse set of parameters that govern its performance. It is worth mentioning that ME-SGO's *learning rate* and has been competitive through the performance despite its historical memory update for the *self-introspection factor* only.

VI. CONCLUSION

A. MERITS AND DEMERITS

In order to have a fair conclusion of the performance of the proposed method, it essential to highlight the merits and demerits.

1) MERITS

1) The implementation of multiple strategies in a systematic and a synergetic sequence through the enhanced improving phase and adaptive acquiring phases improved the performance for complex landscapes and enhanced the population diversity.
2) Distance-based strategy adaption and success-based control parameter adaption has been effective at

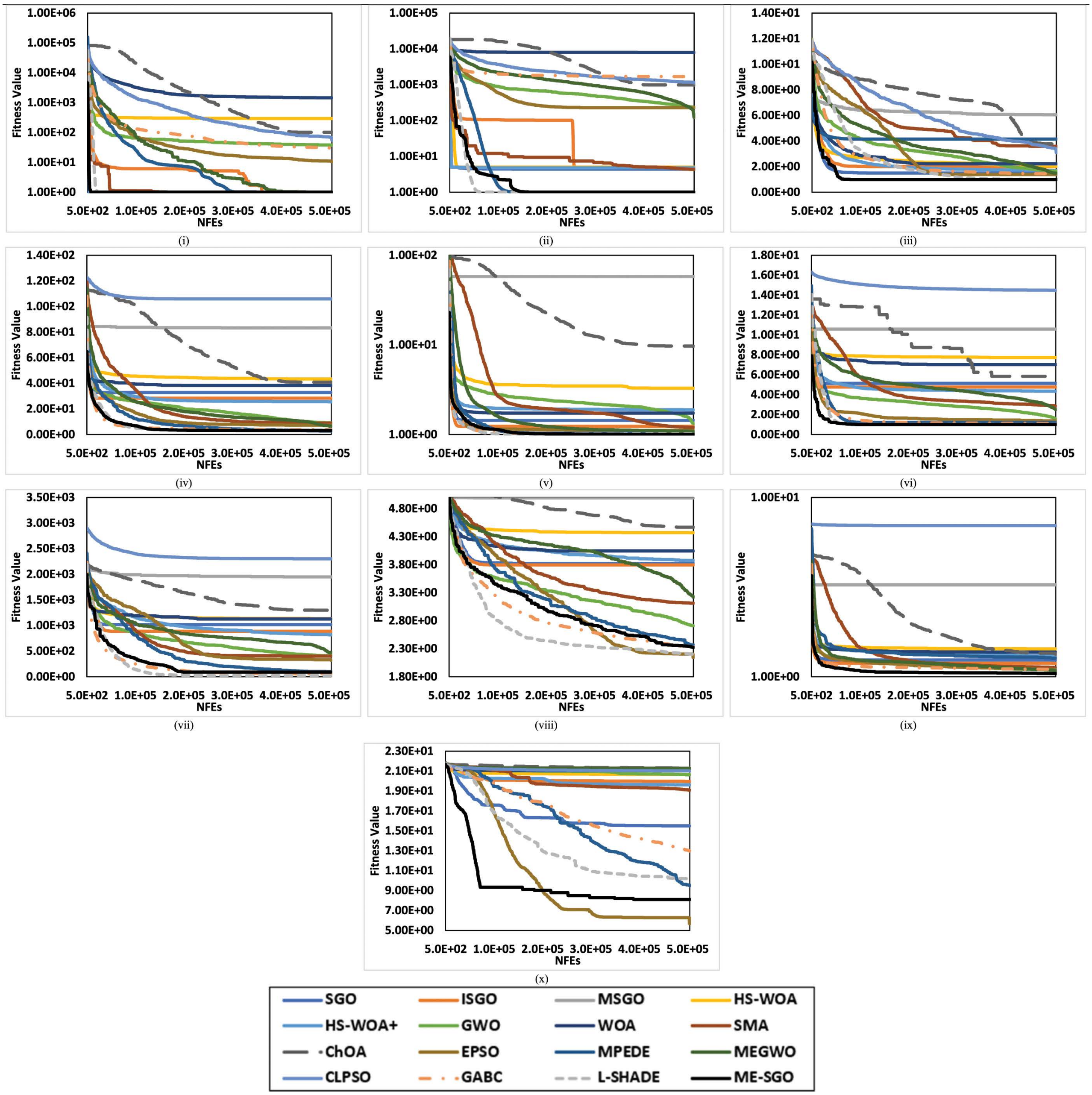

FIGURE 3. Convergence graphs for all the algorithms for the CEC2019 test suite (i)-F1, (ii)-F2, (iii)-F3, (iv)-F4, (v)-F5, (vi)-F6, (vii)-F7, (viii)-F8, (ix)-F9, (x)-F10.

TABLE 33. Tabulation of the best fitness values and the optimal decision variables for the pressure vessel design from the 30 independent runs for the sixteen algorithms.

Algorithms	Optimal values of the decision variables obtained				Optimal Cost obtained
	x_1	x_2	x_3	x_4	
ME-SGO	0.7781682812	0.3846490202	40.3196187249	199.9999999886	5885.3312509799
L-SHADE	0.7781683194	0.3846491385	40.3196217546	199.9999624281	5885.3315367749
SMA	0.7781911246	0.3846677408	40.3207947733	199.9836302354	5885.3917725061
EPSO	0.7790682789	0.3835390181	40.3265516100	200.0000000000	5885.4126540000
MPEDE	0.7781789626	0.3847126600	40.3198059635	200.0000000000	5885.6218583630
ISGO	0.7785492563	0.3848373619	40.3393535046	199.7254605381	5885.9827864557
SGO	0.7789828775	0.3850503833	40.3617615120	199.4172011306	5886.8003560724
GWO	0.7803944074	0.3872439173	40.4336569413	198.5037376570	5895.5021011051
MEGWO	0.7800290558	0.3913500990	40.4036169655	198.8907289971	5908.1870610321
HS-WOA+	0.7838000081	0.3870227515	40.3373777525	200.0000000000	5935.9986303480
CLPSO	0.7928677716	0.3959403175	40.9811503347	191.0991108127	5938.5252788359
HS-WOA	0.8022162404	0.4003687934	41.5135426984	186.1506228021	5994.6720636824
GABC	0.8370596646	0.4172763510	43.1007838727	165.5321749367	6061.6997485320
WOA	1.0527661415	0.6463225819	50.6670821362	93.1393072078	7483.3366637680
ChOA	1.3044609620	0.6310950066	65.8855370475	10.0000000000	7684.2457795734
MSGO	3.1071272384	0.9799390596	61.9663152398	49.1466155266	25951.381319747

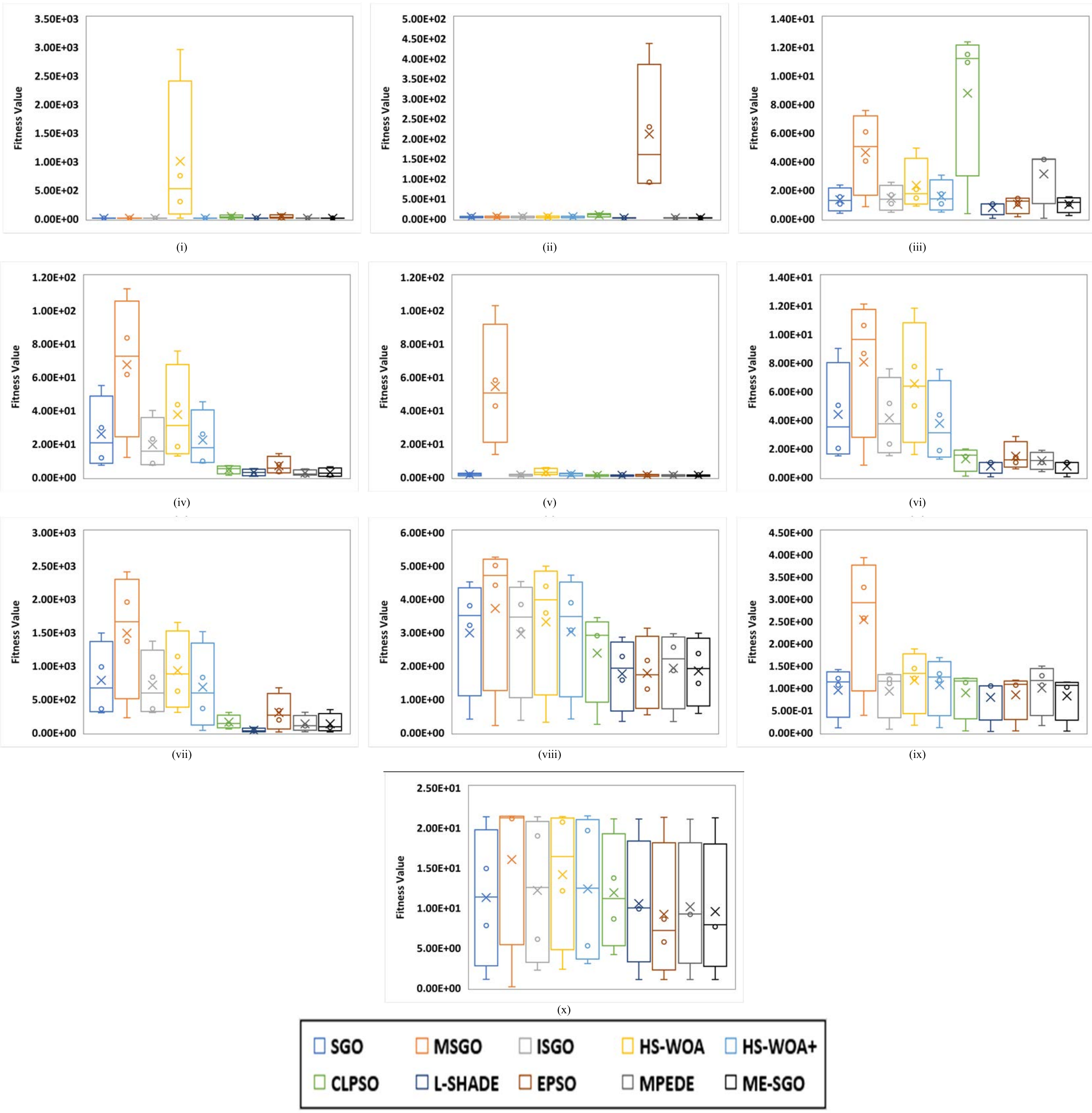

FIGURE 4. Box-plots for the ten best performing algorithms for the CEC2019 test suite (i)-F1, (ii)-F2, (iii)-F3, (iv)-F4, (v)-F5, (vi)-F6, (vii)-F7, (viii)-F8, (ix)-F9, (x)-F10.

achieving a better balance of exploration and exploitation as evident by the performance of the proposed method in the CEC2019 benchmarking suite and the 5 standard engineering problems.

3) Linear population reduction enabled higher settings of population size and iterations and expanded the exploration range while allowing a smoother transition from exploration to exploitation towards the end of the search process.

4) The performance of ME-SGO for the four complex EV optimization problems has been excellent with higher optimality and better robustness to complex and composite landscapes.

2) DEMERITS

1) Slower convergence as a consequence of increased emphasis on exploration over exploitation has been

TABLE 34. The optimization model for the welded beam design.

F.	Objective Function and Constraints	Range of decision variables
SE2	Welded Beam Design Optimization	
	Minimize $O(\vec{X}) = (1.10471x_1^2x_2) + (0.04811x_3x_4(14 + x_2))$	
	Subject to the constraints $c_1(\vec{X}) = \beta(\vec{X}) - \beta_{max} \leq 0$ $c_2(\vec{X}) = \varepsilon(\vec{X}) - \varepsilon_{max} \leq 0$ $c_3(\vec{X}) = \delta(\vec{X}) - \delta_{max} \leq 0$ $c_4(\vec{X}) = x_1 - x_4 \leq 0$ $c_5(\vec{X}) = P - P_C \leq 0$ $c_6(\vec{X}) = 0.125 - x_1 \leq 0$ $c_7(\vec{X}) = (1.10471x_1^2x_2) + (0.04811x_3x_4(14 + x_2)) - 5 \leq 0$ Where $\beta(\vec{X}) = \sqrt{(\beta')^2 + 2\beta'\beta''\frac{x_2}{2R} + (\beta'')^2}$ and $\beta' = \frac{P}{\sqrt{2}x_1x_2},\ \beta'' = \frac{MR}{J},\ M = P\left(L + \frac{x_2}{2}\right)$ $R = \sqrt{\frac{x_2^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2}$ and $J = 2\left\{\sqrt{2}x_1x_2\left[\frac{x_2^2}{4} + \left(\frac{x_1 + x_3}{2}\right)^2\right]\right\}$ $\varepsilon(\vec{X}) = \frac{6PL}{x_4x_3^2}$ and $\delta(\vec{X}) = \frac{6PL^3}{Ex_4x_3^2}$ $P_C(\vec{X}) = \frac{4.013E\sqrt{\frac{x_3^2x_4^6}{36}}}{L^2}\left(1 - \frac{x_3}{2L}\sqrt{\frac{E}{4G}}\right)$ and $P = 6000lb,$ $L = 14in.,$ $\delta_{max} = 0.25in.,$ $E = 30 \times 1^6psi,$ $G = 12 \times 10^6psi,$ $\beta_{max} = 13{,}600\ psi,$ $\varepsilon_{max} = 30{,}000\ psi$	$0.1 \leq x_1 \leq 2$ $0.1 \leq x_2 \leq 10$ $0.1 \leq x_3 \leq 10$ $0.1 \leq x_4 \leq 2$
Description: The welded design requires the optimization (minimization) of the cost of fabrication of a welded beam through four decision variables to be optimized. The four decision variables (x_1, x_2, x_3 and x_4) include the thickness of the weld, the length of the clamped bar, the height of the bar and the thickness of the bar within specified lower and upper bounds. Four inequality constraints with respect to the four decision variables which include the bending stress (α), shear stress (β), buckling load (γ) and the end deflection of the beam (δ) are laid down.		

TABLE 35. Tabulation of the best fitness values and the optimal decision variables for the welded beam design from the 30 independent runs for the sixteen algorithms.

Algorithms	Optimal values of the decision variables obtained				Optimal Cost obtained
	x_1	x_2	x_3	x_4	
SGO	0.205729639786	3.470488665628	9.036623910359	0.205729639786	1.724852308598
MEGWO	0.205729639786	3.470488665626	9.036623910355	0.205729639786	1.724852308598
ISGO	0.205729639788	3.470488665660	9.036623910327	0.205729639788	1.724852308612
MPEDE	0.205729639735	3.470488669290	9.036623910305	0.205729639807	1.724852309168
EPSO	0.205729644130	3.470488609296	9.036623814935	0.205729644135	1.724852324311
L-SHADE	0.205729629722	3.470488896939	9.036624008583	0.205729640035	1.724852343100
ME-SGO	0.205725750736	3.470558060199	9.036674973861	0.205730611484	1.724871835211
SMA	0.205541813735	3.474503364184	9.036715217272	0.205730204073	1.725122680601
GWO	0.204870439260	3.490952548125	9.035353447526	0.205789373499	1.726513146163
HSWOA+	0.204724947482	3.483357707177	9.121718429369	0.205449315717	1.737592490297
HSWOA	0.207753495745	3.453823510348	8.987618310416	0.208528668208	1.738433726812
CLPSO	0.206915230712	3.492138784588	9.018734517472	0.207430907271	1.739503230175
GABC	0.195750406663	3.704450494020	9.024346408909	0.206319614941	1.742705066714
ChOA	0.191848464674	3.943629737186	9.365289959508	0.207876774719	1.840979960093
WOA	0.177997882467	4.785982588218	9.999795096353	0.201381484025	1.987548929145
MSGO	0.375219107067	3.700188877333	7.282550204390	0.379608105450	2.929635331295

TABLE 36. The optimization model for the cantilever beam design.

F.	Objective Function and Constraints	Range of decision variables
SE3	Tension/Compression Spring Design	$0.01 \leq x_1 \leq 100$ $0.01 \leq x_2 \leq 100$ $0.01 \leq x_3 \leq 100$ $0.01 \leq x_4 \leq 100$ $0.01 \leq x_5 \leq 100$
	Minimize $O(\vec{X}) = 0.6224(x_1 + x_2 + x_3 + x_4 + x_5)$	
	Subject to the constraints $c_1(\vec{X}) = \frac{61}{x_1^3} + \frac{27}{x_2^3} + \frac{19}{x_3^3} + \frac{7}{x_4^3} + \frac{1}{x_5^3} - 1 \leq 0$	
Description: In this problem, the goal is to minimize the weight of a cantilever beam with hollow square blocks. There are five squares of which the first block is fixed, and the fifth one bur- dens a vertical load, box girders, and lengths of those girders are design parameters for this problem.		

witnessed for simple unimodal and multi-modal landscapes.

2) The *learning rate* proposed for parameter adaption may be slower to adapt to other complex landscapes and could require experimentations with different settings to extract the best performance.

B. SUMMARY

1) ME-SGO ranked second for the CEC2019 suite and performed competitively with the other state-of-the-art optimization algorithms outperforming the variants of SGO and other modern meta-heurists.

TABLE 37. Tabulation of the best fitness values and the optimal decision variables for the cantilever beam design from the 30 independent runs for the sixteen algorithms.

Algorithms	Optimal values of the decision variables obtained					Optimal Cost obtained
	x_1	x_2	x_3	x_4	x_5	
ME-SGO	6.01608629860	5.30925862922	4.49419514159	3.50148343800	2.15263613412	1.33995636163
L-SHADE	6.01783656600	5.30578411755	4.49542100073	3.50215706739	2.15246713975	1.33995675163
ISGO	6.02314820845	5.30528663031	4.48993912642	3.50579287053	2.14955936336	1.33996051482
MPEDE	6.02652833984	5.31031885086	4.48184310132	3.50260431886	2.15251419350	1.33996566939
EPSO	6.01407065947	5.30833739598	4.49230687738	3.51496334790	2.14415588256	1.33996725179
SGO	6.02323475221	5.31174073707	4.48628321258	3.50250811775	2.14995824565	1.33996944407
GWO	6.02373635714	5.30852104375	4.50460241729	3.49251391494	2.14463461785	1.33997812110
MEGWO	6.00458011307	5.32307332981	4.50257342622	3.47953686645	2.16446466231	1.33999185203
CLPSO	5.97585307641	5.33140624108	4.55080298565	3.47420660533	2.14431005664	1.34013852742
HSWOA	6.05177969552	5.31537111398	4.43524922699	3.50883134274	2.17025214016	1.34044457161
HSWOA+	5.85901302713	5.48242025719	4.47372880705	3.54249350809	2.13815663351	1.34133868334
GABC	6.07549533032	4.96762959059	4.90540806006	3.61497880957	2.04760998181	1.34853399859
ChOA	5.74001572365	5.72804605094	4.42899251827	3.71626044711	2.01114920858	1.34936655039
WOA	5.52172189427	5.63614527974	6.16663606745	3.05547988002	2.12241737286	1.40414979085
SMA	5.01493032737	5.01493032737	5.01493032737	5.01493032737	5.01493032737	1.56465826214
MSGO	11.02138451371	7.61351236354	5.01551690644	3.27943902759	1.61871395751	1.78143056637

TABLE 38. The optimization model for the tension/compression spring design.

F.	Objective Function and Constraints	Range of decision variables
SE4	Tension/Compression Spring Design	
	Minimize $O(\vec{X}) = (x_3+2)x_2x_1^2$	
	Subject to the constraints $c_1(\vec{X}) = 1 - \frac{x_2^3 x_3}{71785 x_1^4} \le 0$ $c_2(\vec{X}) = \frac{4x_2^2 - x_1x_2}{12566(x_2x_1^3 - x_1^4)} + \frac{1}{5108x_1^2} \le 0$ $c_3(\vec{X}) = 1 - \frac{140.45x_1}{x_2^2x_3} \le 0$ $c_4(\vec{X}) = \frac{x_1+x_2}{1.5} - 1 \le 0$	$0.05 \le x_1 \le 2.00$ $0.25 \le x_2 \le 1.30$ $2.00 \le x_3 \le 15.0$
Description: The tension/compression spring design requires the optimization (minimization) of the weight of a compression spring through three decision variables to be optimized. The three decision variables (x_1, x_2, and x_3) include the wire diameter, mean coil diameter and the number of active coils within specified lower and upper bounds. Four inequality constraints with respect to the three decision variables which include the surge frequency, deflection and shear stress are laid down. In this problem, the constraints are normalized and the static penalty method is utilized to generate a feasible optimal solution.		

TABLE 39. Tabulation of the best fitness values and the optimal decision variables for the tension/compression spring design from the 30 independent runs for the sixteen algorithms.

Algorithms	Optimal values of the decision variables obtained			Optimal Cost obtained
	x_1	x_2	x_3	
ME-SGO	0.0516890623	0.3567177688	11.2889640502	0.0126652328
L-SHADE	0.0516873555	0.3566767027	11.2913732742	0.0126652342
ISGO	0.0516506892	0.3557953157	11.3432502045	0.0126652597
WOA	0.0519380089	0.3627363483	10.9447913663	0.0126665028
SGO	0.0513475016	0.3485560775	11.7840089895	0.0126673813
MPEDE	0.0512826588	0.3470152271	11.8821951184	0.0126691577
SMA	0.0521846822	0.3687580726	10.6168506086	0.0126700574
MEGWO	0.0525558860	0.3779317526	10.1456296980	0.0126787413
GWO	0.0509080021	0.3378948775	12.5072812460	0.0127039784
EPSO	0.0501031302	0.3197440986	13.8386810681	0.0127130944
GABC	0.0523911704	0.3732778932	10.4101998788	0.0127153186
HSWOA+	0.0527609586	0.3829447589	9.9436215508	0.0127320260
CLPSO	0.0531718848	0.3928439008	9.4714616898	0.0127409815
HSWOA	0.0500000000	0.3169559645	14.0958906338	0.0127542214
ChOA	0.0500000000	0.3167878406	14.2154142695	0.0128421152
MSGO	0.0651257759	0.6998258154	5.0748812286	0.0209997891

TABLE 40. Problem description for the 10-bar truss design.

Description:
In truss bar optimization, it required to minimize the structural weight of the truss bars with respect to the constraints on the design, stress, deflection, displacement etc. The decision variable corresponding to the dimensions so the truss bars whose count can be 10, 15, 25, 50, 72, 200. The truss bar optimization applies to the continuous and discrete decision variables and the 10-bar truss optimization for continuous variables is considered in the current testing. A detailed description of the mathematical formulation, the objective function is available at [78]. The basic description of the constraints and the range of the decision variables are provided below.

Description of the constraints:
The variation of cross-sectional areas is from 0.1 in^2 to 35.0 in^2.
The unit weight of the material is 0.1 lb/in^3
The modulus of elasticity is 107 psi.

The design constraints are as follows.
The maximum allowable stress for any member of the truss : ±25 psi.
The maximum deflection at any node : ±2.0 mm.

TABLE 41. Tabulation of the best fitness values and the optimal decision variables for the 10-bar truss design from the 30 independent runs for the sixteen algorithms.

Algorithms	Optimal values of the decision variables obtained										Optimized Weight
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	
MPEDE	30.5682	0.1000	23.1626	15.2303	0.1000	0.5597	21.0124	7.4589	0.1000	21.5336	5060.870
ME-SGO	30.3120	0.1012	23.1092	15.0945	0.1000	0.5769	21.0972	7.4622	0.1003	21.7555	5061.302
SMA	30.9114	0.1000	22.8725	14.9962	0.1000	0.5441	21.0258	7.4980	0.1000	21.6299	5061.370
EPSO	30.9635	0.1000	23.3302	15.0945	0.1004	0.5181	21.0176	7.4638	0.1000	21.2615	5061.430
L-SHADE	30.1575	0.1015	23.1219	15.2116	0.1002	0.6079	21.2881	7.4871	0.1001	21.5443	5061.767
GWO	31.4315	0.1391	23.3237	14.6359	0.1095	0.3263	21.1417	7.5177	0.1082	21.4640	5076.252
GABC	31.2108	0.1000	24.4742	15.0265	0.1000	0.1000	20.1160	8.1739	0.1000	21.3679	5089.668
HSWOA+	27.7942	0.1076	23.3847	14.7782	0.2115	0.1076	21.6980	8.7994	0.1089	23.1653	5130.602
ChOA	33.5000	0.1053	20.2883	17.1178	0.1438	0.3481	21.4468	8.8938	0.1280	19.7748	5147.704
CLPSO	27.2978	0.1885	25.4958	14.4022	0.1160	0.4145	21.5567	8.2853	0.4442	22.4650	5152.701
MEGWO	23.1222	0.1264	29.3687	18.3397	0.1179	1.2017	27.1991	7.5460	0.1265	18.7025	5345.136
SGO	33.5000	0.1000	18.4241	11.7326	0.3903	0.1000	18.8339	10.8065	0.4987	33.5000	5552.864
WOA	23.0609	0.1052	21.2476	17.5273	0.8970	0.1000	24.5312	21.6694	0.1000	24.7826	5884.731
HSWOA	28.6169	5.3381	24.1371	11.0118	0.2042	16.9766	18.2720	10.1768	4.0180	29.1434	6244.410
ISGO	25.6920	8.8942	26.2481	12.1754	0.1000	3.6401	16.2450	21.8636	22.0966	13.2559	6504.340
MSGO	31.8284	6.8907	23.2485	7.5114	7.6822	11.6410	14.9534	16.7718	14.1246	16.2059	6909.093

TABLE 42. Description of the problem formulation, objectives and constraints for the OPF (IEEE 30 and IEEE 57 bus systems).

Problem Formulation

The combination of power flow equation and economic dispatch equation can be simplified into non-linear function. Standard OPF problem can be formulated to minimize the objective in the system and satisfy system equality and inequality constrains as: Mathematically, OPF is represented as:

$$\text{Minimize}: f(x,u) \quad \text{subject to}: \begin{matrix} g(x,u) \le 0 \\ h(x,u) = 0 \end{matrix} \qquad \text{A(1)}$$

where,
u is the vector of control or independent variables, x is the vector of state or dependent variables. $f(x,u)$: objective functions of OPF, g (x,u): set of inequality constraints, $h(x,u)$: set of equality constraints.

Control (independent) variables

The set of variables that can control the power flow in the network is represented in vector form as:

$$u = [P_{G_2}\ldots P_{G_{NG}}, V_{G_1}\ldots V_{G_{NG}}, Q_{C_1}\ldots Q_{C_{NC}}, T_1\ldots T_{NT}] \qquad \text{A(2)}$$

where,
P_{Gi} is the ith bus generator active power (except swing generator). Selection of bus 1 as swing bus is representative only and swing bus can be any one of the generator buses. V_{Gi} is the voltage magnitude at ith PV bus (generator bus), T_j is the jth branch transformer tap, Q_{Ck} is the shunt compensation at kth bus. NG, NC and NT are the number of generators, shunt VAR compensators and transformers respectively. A control variable can assume any value within its range. In reality, transformer taps are not continuous. However, the tap settings expressed here are in p.u. and absolute value of voltage is not accounted for. Hence for study purpose and to compare with past reported results, all control variables including tap settings are considered continuous for most of the study cases. Discrete steps for transformers and shunt capacitors are accounted only in one special study case.

State (dependent) variables

The state of power system is defined by the state variables which can be expressed by vector x as:

$$x = [P_{G_1}, V_{L_1}\ldots V_{L_{NL}}, Q_{G_1}\ldots Q_{G_{NG}}, S_{l_1}\ldots S_{l_{nl}}] \qquad \text{A(3)}$$

where,
P_{G1} is the generator active power at slack (or swing) bus, Q_{Gi} is the reactive power of generator connected to bus i, VLp is the bus voltage of pth load bus (PQ bus) and line loading of qth line is given by S_{lq} . NL and nl are the number of load buses and transmission lines respectively.

Objectives

Case 1

Minimization of fuel cost

$$f(x,u) = \sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \qquad \text{A(4)}$$

where,
a_i, b_i and c_i are the cost coefficients of the ith generator producing output power P_{G_i}

Case 2

Enhancement of voltage stability of the network

If a power system has NL number of load (PQ) buses and NG number of generator (PV) buses, the value of L-index Lj of bus j is defined as:

$$L_j = \left| 1 - \sum_{i=1}^{NG} F_{ji} \frac{V_i}{V_j} \right| \qquad \text{A(5)}$$

where j=1, 2, …. , NL
and
$F_{ji} = -[Y_{LL}]^{-1}[Y_{LG}]$

where,
sub-matrices Y_{LL} and Y_{LG} are obtained from system YBUS matrix after separating load (PQ) buses and generator (PV) buses given as follows.

$$\begin{bmatrix} I_L \\ I_G \end{bmatrix} = \begin{bmatrix} Y_{LL} & Y_{LG} \\ Y_{GL} & Y_{GL} \end{bmatrix} \begin{bmatrix} V_L \\ V_G \end{bmatrix} \qquad \text{A(6)}$$

L-index of each bus serves as a good indicator of power system stability. The value of the index varies from 0 to 1, with 0 being the no load case while 1 signifies voltage collapse.
The L-index is calculated for all load buses and maximum value out of those acts as the global indicator for the system stability.

Therefore, the objective function of system stability is given by:

$$f(x,u) = L_{max} = max(L_j) \qquad \text{A(7)}$$

where j=1, 2, …. , NL

Case 3

Minimization of fuel cost

$$f(x,u) = Emission = \sum_{i=1}^{NG} \left[\left(\alpha_i + \beta_i P_{G_i} + \gamma_i P_{G_i}^2 \right) \times 0.01 + \omega_i e^{(\mu_i P_{G_i})} \right] \qquad \text{A(8)}$$

where,
α_i, β_i, γ_i, ω_i and μ_i are all emission coefficients.

Case 4

Minimization of real power loss

$$f(x,u) = P_{loss} = \sum_{q=1}^{nl} G_{q(ij)} \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\delta_{ij}) \right] \qquad \text{A(9)}$$

where,
$\delta_{ij} = \delta_i - \delta_j$, , is the difference in voltage angles between bus i and bus j and $G_{q(ij)}$ is the transfer conductance of branch q connecting buses i and j.

Case 5

Minimization of fuel cost considering valve point effect

$$f(x,u) = \sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 + \left| d_i \times \sin\left(e_i \times \left(P_{G_i}^{min} - P_{G_i} \right) \right) \right| \qquad \text{A(10)}$$

where,
d_i and e_i are the coefficients that represent the valve-point loading effect.

Case 6

Minimization of fuel cost and real power loss

$$f(x,u) = \sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 + \lambda_P \times P_{loss} \qquad \text{A(11)}$$

where,
P_{loss} is is the real power loss in the network calculated and value of factor λ_P is chosen as 40.

Case 7

Minimization of fuel cost and voltage deviation

Voltage deviation is expressed as:

$$VD = \left[\sum_{p=1}^{NL} \left| V_{L_p} - 1 \right| \right] \qquad \text{A(12)}$$

The combined objective function of fuel cost and voltage deviation is:

$$f(x,u) = \left[\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \right] + \lambda_{VD} \times VD \qquad \text{A(13)}$$

where,
weight factor λ_{VD} is assigned a value of 100 based on the previous implementations.

TABLE 42. *(Continued.)* **Description of the problem formulation, objectives and constraints for the OPF (IEEE 30 and IEEE 57 bus systems).**

Case 8	**Minimization of fuel cost and enhancement of voltage stability** $f(x,u) = \left[\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2\right] + \lambda_L \times L_{max}$ where, value of weight factor λ_L is 100.	A(14)
Case 9	**Minimization of fuel cost, emission, voltage deviation and losses** $f(x,u) = \left[\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2\right] + [\lambda_E \times Emission] + [\lambda_{VD} \times L_{max}] + [\lambda_p \times P_{loss}]$ where, the weight factors are selected as λ_E = 19, λ_{VD} = 21 and λ_p =22 based on the previous implementations.	A(15)
Constraints		
Equality Constraints	In OPF, power balance equations are the equality constraints and those are represented as: $P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{NB} V_j[G_{ij}\cos(\delta_{ij}) + B_{ij}\sin(\delta_{ij})] = 0$ $Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{NB} V_j[G_{ij}\sin(\delta_{ij}) - B_{ij}\cos(\delta_{ij})] = 0$ where, $\delta_{ij} = \delta_i - \delta_j$, is the difference in voltage angles between bus i and bus j, NB is the number of buses, P_D and Q_D are active and reactive load demands, respectively. G_{ij} is the transfer conductance and B_{ij} is the susceptance between bus i and bus j, respectively.	A(16) A(17)
Inequality Constraints	(a) Generator Constraints : $V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max}$ $P_{G_i}^{min} \le P_{G_i} \le P_{G_i}^{max}$ $Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max}$ (b) Transformer constraints: $T_j^{min} \le T_j \le T_j^{max}$ (c) Shunt compensator constraints: $Q_{C_k}^{min} \le Q_{C_k} \le Q_{C_k}^{max}$ (d) Security constraints: $V_{L_p}^{min} \le V_{L_p} \le V_{L_p}^{max}$ $S_{l_q} \le S_{l_q}^{max}$	A(18) A(19) A(20) A(21)

TABLE 43. **Summary of the IEEE 30 bus system with EV loading at the residential buses.**

Summary of IEE 30-Bus System		
Bus System	**IEEE 30-bus system**	
	Quantity	**Details**
Buses	30	
Branches	41	
Generators	6	Buses: 1 (swing), 2, 5, 8, 11 and 13
Shunt VAR compensation	9	Buses: 10, 12, 15, 17, 20, 21, 23, 24 and 29
Transformer with tap changer	4	Branches: 11, 12,15 and 36
Control variables	24	–
Connected load	–	283.4 MW, 126.2 MVAr
Load bus voltage range allowed	24	[0.95 – 1.05] p.u.
Residential buses	19	2,3,5,6,7,8,9,10,13,14,15,16,17,20,21,23,24
Commercial buses	5	4,11,12,18,19
Industrial buses	6	22,26,27,28,29,30

TABLE 44. **Summary of the IEEE 57 bus system with EV loading at the residential buses.**

Summary of IEE 57-Bus System		
Bus System	**IEEE 57-bus system**	
	Quantity	**Details**
Buses	57	
Branches	80	
Generators	7	Buses: Buses: 1 (swing), 2, 3, 6, 8, 9 and 12
Shunt VAR compensation	3	Buses: 18, 25 and 53
Transformer with tap changer	17	Branches: 19, 20, 31, 35, 36, 37, 41, 46, 54, 58, 59, 65, 66, 71, 73, 76 and 80
Control variables	33	–
Connected load	–	1250.8 MW, 336.4 MVAr
Load bus voltage range allowed	50	[0.94 – 1.06] p.u.
Residential buses	42	2,3,5,6,8,9,10,12,13,14,15,16,17,18,19,20,23,25,27,28,29,30,31,32,33,35,38,41,42,43,44,47,59,50,51,52,53,54,55,56,57
Commercial buses	8	4,7,11,21,22,24,26,34
Industrial buses	7	36,37,39,40,45,46,48

TABLE 45. **Lower and Upper bunds for the OPF (IEEE 30 and IEEE 57 bus systems).**

Bus System	**IEEE 30 Bus System**	**IEEE 57 Bus System**
Dimension of optimization problem (D)	24	33
Optimization cases	9 Cases	9 Cases
Lower Bound (lb)	[20 15 10 10 12 0.95 0.95 0.95 0.95 0.95 0.95 0 0 0 0 0 0 0 0 0 0.9 0.9 0.9 0.9]	[30 40 30 100 30 100 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0 0 0 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9 0.9]
Upper Bound (ub)	[80 50 35 30 40 1.1 1.1 1.1 1.1 1.1 1.1 5 5 5 5 5 5 5 5 5 1.1 1.1 1.1 1.1]	[100 140 100 550 100 410 1.1 1.1 1.1 1.1 1.1 1.1 1.1 20 20 20 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1]

TABLE 46. Tabulation of the best solutions of OPF with EV loading for the IEEE 30-bus system.

Decision Variables	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
Algorithm with the best Fitness	ME-SGO	MPEDE	EPSO	ME-SGO	ME-SGO	MPEDE	ME-SGO	ME-SGO	MPEDE
*PG*2 (MW)	50.09724	66.23146	72.58317	79.99757	52.37577	58.20856	50.41160	50.29838	53.54648
*PG*5 (MW)	21.84629	38.29814	50.00000	50.00000	19.50602	39.63774	22.14769	21.84235	32.53365
*PG*8 (MW)	24.11942	19.14397	35.00000	34.99980	11.18321	34.95943	24.93002	23.75930	34.97054
*PG*11 (MW)	12.89832	18.17935	30.00000	29.99994	10.02351	29.98700	13.72408	12.92313	29.91544
*PG*13 (MW)	12.10041	16.10453	40.00000	40.00000	12.02962	30.25099	12.02439	12.30661	23.22247
*V*1 (p.u.)	1.08464	1.06250	1.06357	1.06293	1.09134	1.07075	1.04499	1.08488	1.07066
*V*2 (p.u.)	1.06483	1.04935	1.05750	1.05792	1.06773	1.05868	1.02609	1.06437	1.05788
*V*5 (p.u.)	1.03398	1.01886	1.03773	1.03807	1.03310	1.03390	1.01228	1.03279	1.03011
*V*8 (p.u.)	1.03741	1.04100	1.04201	1.04312	1.03439	1.04037	1.00414	1.03714	1.04146
*V*11 (p.u.)	1.08404	1.09760	1.09193	1.06199	1.08212	1.08964	1.05313	1.09057	1.03158
*V*13 (p.u.)	1.04557	1.06867	1.05050	1.05704	1.04071	1.04844	0.98911	1.04233	1.02362
*Q*c10 (MVAr)	3.73786	4.86662	5.00000	4.99111	0.00000	4.78691	5.00000	1.30638	0.21191
*Q*c12 (MVAr)	0.00000	0.46287	5.00000	0.63304	2.78767	1.55766	0.00000	3.44145	4.52639
*Q*c15 (MVAr)	4.04332	4.92593	5.00000	4.23643	4.12650	4.98683	4.95915	5.00000	1.18132
*Q*c17 (MVAr)	4.76420	2.52490	4.25269	4.99661	4.09129	0.10129	0.04391	4.69254	4.58424
*Q*c20 (MVAr)	3.89588	3.23265	5.00000	3.53728	4.34602	4.73458	4.97178	3.26727	4.25975
*Q*c21 (MVAr)	4.92043	4.45622	4.99810	4.98550	4.79385	4.75366	4.98735	4.70800	4.80023
*Q*c23 (MVAr)	3.61329	4.94168	0.00000	3.24956	2.78302	2.66965	4.98697	2.35132	4.30145
*Q*c24 (MVAr)	4.96530	0.00000	4.90768	4.99459	4.58987	4.81017	4.97979	5.00000	4.82381
*Q*c29 (MVAr)	2.09811	0.04732	2.45834	2.02607	2.11116	2.56025	2.39889	1.95373	1.52983
*T*11 (p.u.)	1.07846	1.04111	1.01054	1.07277	1.03424	1.08473	1.07430	1.06145	1.08499
*T*12 (p.u.)	0.90000	0.91971	1.03748	0.90282	0.92788	0.90006	0.90047	0.90429	0.94522
*T*15 (p.u.)	0.96465	1.01994	0.98656	0.99249	0.95933	0.97674	0.93591	0.96778	1.01222
*T*36 (p.u.)	0.97269	0.95636	0.97750	0.97408	0.97713	0.97428	0.96879	0.96859	0.99440
Fuel cost ($/h)	839.0224	914.7841	980.4872	994.3924	842.6901	900.2565	842.1262	839.0393	871.4625
Emission (t/h)	0.380702	0.264215	0.208744	0.209634	0.442874	0.232734	0.378727	0.380442	0.255242
***P*loss (MW)**	9.49952	6.809632	3.629422	3.514513	11.11823	4.913702	10.29822	9.503517	5.931483
VD (p.u.)	0.872397	0.87015	0.822999	0.881501	0.650641	0.822314	0.116209	0.90461	0.334295
L-index (max)	0.140281	0.13955	0.141495	0.140809	0.142891	0.141016	0.150708	0.139828	0.148688
Fitness	838.9998	0.139465	0.208744	3.513195	872.8843	1095.754	852.2779	852.9959	1013.00
Computational Time (Sec)	78.69122	159.09770	201.30660	164.53972	160.93747	173.72671	183.94840	79.27672	158.82472

TABLE 47. Tabulation of the best solutions of OPF with EV loading for the IEEE 57-bus system.

Decision Variables	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
Algorithm with the best Fitness	ME-SGO	ME-SGO	EPSO	GABC	ME-SGO	ME-SGO	GABC	ME-SGO	ME-SGO
*PG*2 (MW)	94.42275	30.00000	100.00000	82.89066	97.07486	99.98141	88.37982	77.86440	90.36065
*PG*3 (MW)	50.97090	135.99660	140.00000	53.42610	48.22898	43.99692	46.00397	42.55337	42.81557
*PG*6 (MW)	67.93696	100.00000	100.00000	93.13912	93.88533	98.56691	92.86857	57.65268	91.69903
*PG*8 (MW)	495.34330	344.76490	299.88020	456.41190	471.33810	472.00580	451.92760	471.85510	466.95830
*PG*9 (MW)	98.17355	95.83190	100.00000	100.00000	100.00000	99.82678	100.00000	90.59551	100.00000
*PG*12 (MW)	386.10320	409.97620	387.36120	410.00000	380.89750	379.76440	410.00000	259.31380	400.52470
*V*1 (p.u.)	0.99502	0.99331	1.09811	1.03548	0.97649	0.99830	1.07383	1.03292	1.00417
*V*2 (p.u.)	0.98606	0.98323	1.08077	1.02284	0.96797	0.99462	1.06476	0.95054	0.99619
*V*3 (p.u.)	0.97157	0.98922	1.05887	1.01981	0.96559	0.98722	1.04845	1.01046	0.99305
*V*6 (p.u.)	0.98692	0.99350	1.06333	1.05619	0.99649	1.00266	1.05337	0.99985	0.99513
*V*8 (p.u.)	1.00370	0.99175	1.06900	1.09264	1.00700	1.01061	1.05389	1.01274	0.99894
*V*9 (p.u.)	0.97359	0.96764	1.03973	1.05413	0.97134	0.97330	1.02895	1.06662	0.97382
*V*12 (p.u.)	0.98087	0.98154	1.02191	1.05197	0.97936	0.96966	1.04009	0.99468	0.99292
*Q*c18 (MVAr)	0.95174	17.49478	19.99520	15.48706	16.58017	16.90480	0.00000	2.78452	13.64522
*Q*c25 (MVAr)	12.67660	17.76321	9.35225	5.83905	17.68960	11.16725	4.72516	19.26765	13.64125
*Q*c53 (MVAr)	5.86649	15.02542	12.75411	2.28212	14.01502	14.10361	16.01252	19.42521	13.76410
*T*19 (p.u.)	0.91341	1.04653	0.97321	0.90000	0.97662	0.91034	0.96050	1.03780	0.90000
*T*20 (p.u.)	0.90469	0.93643	1.04262	1.10000	0.90738	1.00138	0.94428	0.95410	1.01869
*T*31 (p.u.)	1.07233	1.05469	1.10000	1.03890	1.00254	0.95503	1.10000	0.96021	0.94374
*T*35 (p.u.)	1.05762	0.91454	1.00784	0.93839	1.05691	1.07126	1.02892	1.08984	0.92967
*T*36 (p.u.)	0.90535	1.09236	1.02842	0.92144	1.01855	0.90020	0.90000	1.02730	0.99004
*T*37 (p.u.)	1.04181	0.97257	1.10000	1.04747	1.03979	1.02416	1.02944	1.01050	0.99250
*T*41 (p.u.)	0.91515	0.96547	0.99015	0.98292	0.93296	0.93491	1.01109	0.97427	0.93044
*T*46 (p.u.)	0.94340	0.90000	0.90000	0.95732	0.94538	0.97954	0.95884	0.90939	0.98537
*T*54 (p.u.)	0.92907	0.90895	0.91815	0.90000	0.90000	0.90297	0.90425	0.90322	0.91743
*T*58 (p.u.)	0.90281	0.90921	0.98741	0.98873	0.90000	0.90322	0.98949	0.90381	0.92938
*T*59 (p.u.)	0.90207	0.90036	0.94641	0.95351	0.91385	0.90147	0.97216	0.99780	0.90052
*T*65 (p.u.)	0.91382	0.90063	1.08841	1.03655	0.90262	0.90142	0.96045	1.00211	0.96662
*T*66 (p.u.)	0.90429	0.90391	0.92735	0.97246	0.90000	0.90000	0.90000	0.90165	0.90000
*T*71 (p.u.)	0.90000	0.90240	1.01384	0.97759	0.92881	0.90350	1.01823	0.97388	0.90213
*T*73 (p.u.)	0.95748	1.09264	0.90000	0.98747	1.05687	0.97407	1.04952	1.04051	1.01094
*T*76 (p.u.)	0.91596	0.91734	1.10000	0.98816	0.96821	0.93492	0.90000	0.90255	0.93658
*T*80 (p.u.)	0.95225	0.94319	1.10000	1.03208	0.93794	0.94958	0.98591	1.04792	0.91495
Fuel cost ($/h)	44915.54	45060.36	48351.90	45071.52	44899.31	44857.83	45165.958	46393.1	44928.24
Emission (t/h)	1.512167	1.625308	1.116408	1.428393	1.487879	1.45100	1.7173888	1.741472	1.595312
***P*loss (MW)**	22.16468	25.15457	20.20402	21.30668	21.46148	21.35757	27.093766	42.41244	23.29527
VD (p.u.)	1.293303	1.449709	1.561037	1.393597	1.320027	1.274951	1.6749556	0.730941	1.55910
L-index (max)	0.373453	0.378041	0.364649	0.369802	0.371187	0.375976	0.370031	0.376513	0.376258
Fitness	44879.3	16.1845	1.116403	46808.0	44990.1	44956.5	44905.5	0.698257	45321.2
Computational Time (Sec)	186.20	237.84	230.23	241.71	248.36	263.02	239.22	286.74	292.84

2) ME-SGO achieved the perfect precision of 10 digits for 6 out of the 10 functions from CEC2019 suite and scored 68 points out of 100 in the 100-digit competition.

3) The performance of ME-SGO for the five engineering problems weas very completive with L-SHADE and MPEDE with lower standard deviations compared to the other state-of-the-art optimizers.

TABLE 48. Description of the objective functions for the two cases, i) Minimization of real power loss and ii) Minimization of voltage deviation for the ORPD (IEEE 30 bus system).

Case 1	**Minimization of real power loss** $f(x,u) = P_{loss} = \sum_{q=1}^{nl} G_{q(ij)}\left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_{ij})\right]$ where, $\delta_{ij} = \delta_i - \delta_j$, , is the difference in voltage angles between bus i and bus j and $G_{q(ij)}$ is the transfer conductance of branch q connecting buses i and j.	A(22)
Case 2	**Minimization of voltage deviation** Voltage deviation is expressed as: $f(x,u) = VD = \left[\sum_{p=1}^{NL} \left\|V_{L_p} - 1\right\|\right]$ where, V_{Lp} is the bus voltage of pth load bus (PQ bus) and NL is the number of load buses.	A(23)

TABLE 49. Lower and upper bunds for the ORPD (IEEE 30 SYSTEM).

Bus System	**IEEE 30 Bus System**
Dimension of optimization problem (D)	19
Optimization cases	2 Cases with 25 Scenarios
Lower Bound (lb)	[0.95 0.95 0.95 0.95 0.95 0.95 0.9 0.9 0.9 0.9 0 0 0 0 0 0 0 0 0]
Upper Bound (ub)	[1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 1.1 5 5 5 5 5 5 5 5 5]

TABLE 50. Description of the 25 different scenarios adopted with EV loading for the ORPD.

Scenario number	% Loading (Residential load+ EV load)	Wind power (MW)	PV power (MW)	Scenario probability, Δ_{sc}
1	105.784	0	50	0.001
2	55.714	26.566	36.349	0.001
3	73.165	42.772	23.805	0.007
4	77.665	0	40.164	0.001
5	99.491	35.666	46.795	0.001
6	60.573	0.912	30.363	0.004
7	97.292	15.645	18.283	0.001
8	58.378	35.892	16.324	0.038
9	98.092	29.805	0	0.006
10	77.942	14.248	37.580	0.002
11	41.386	9.580	9.073	0.004
12	65.615	16.561	43.456	0.001
13	90.475	33.496	22.067	0.003
14	66.773	40.393	50	0.001
15	61.498	32.470	27.564	0.009
16	68.935	18.629	0	0.478
17	67.603	35.103	6.942	0.093
18	71.770	38.528	18.992	0.044
19	79.921	13.102	33.639	0.004
20	72.351	28.152	20.560	0.037
21	78.322	10.458	10.058	0.048
22	66.073	50.441	3.813	0.027
23	74.465	0	11.464	0.071
24	63.754	1.416	25.904	0.012
25	64.487	65.994	13.756	0.106

TABLE 51. Tabulation of the best solutions of ORPD (Scenario 1-12) with EV loading for the IEEE 30-bus system.

Decision Variables	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12
Algorithm with the best Fitness	**ME-SGO**	**ME-SGO**	**ISGO**	**MPEDE**	**ME-SGO**	**ME-SGO**	**ME-SGO**	**ISGO**	**ME-SGO**	**WOA**	**ME-SGO**	**ME-SGO**
$V1$ (p.u.)	0.99299	1.02113	1.04503	1.06843	1.02073	1.00935	1.00851	1.00287	1.02291	1.03323	1.00124	1.00922
$V2$ (p.u.)	1.00402	1.01974	1.03723	1.05916	1.01958	1.01105	1.00989	1.00749	1.02054	1.02790	1.00840	1.01273
$V5$ (p.u.)	1.00249	0.99781	1.01348	1.03371	0.99804	0.99829	0.99688	1.00328	1.00675	1.00772	1.00694	1.00425
$V8$ (p.u.)	1.00414	1.01010	1.02262	1.03714	1.00790	1.00294	1.00124	1.00176	1.00462	1.00766	0.99983	0.99828
$V11$ (p.u.)	0.99121	1.00417	1.05646	1.05642	1.00651	1.01156	1.01207	1.00447	1.02079	1.00806	1.01238	1.01111
$V13$ (p.u.)	1.01150	1.01128	1.02509	1.01679	1.00443	1.00733	1.00247	1.01147	1.01736	1.00972	0.99529	0.99859
$T11$ (p.u.)	0.99268	1.01579	1.01474	1.07584	1.01883	1.02444	1.01783	1.02774	1.03874	1.00696	1.02414	1.01586
$T12$ (p.u.)	0.97340	0.98455	1.03000	0.97168	0.96578	0.95643	0.95318	0.94886	0.92720	1.00732	0.95304	0.95069
$T15$ (p.u.)	1.00447	0.99586	1.02781	1.02804	1.00488	0.98529	0.97176	1.00812	0.99348	1.00434	0.98557	0.98509
$T36$ (p.u.)	0.98592	0.98300	1.00892	0.99466	0.97860	0.97901	0.98888	0.97897	0.98659	1.00589	0.98049	0.98407
$Qc10$ (MVAr)	2.28992	3.71194	2.39395	1.73534	0.00000	2.67366	0.38855	1.45856	0.50780	3.70941	0.14787	0.00000
$Qc12$ (MVAr)	0.33523	0.20268	2.42402	4.41238	3.07541	0.00000	0.00000	1.54003	0.10806	4.23152	4.86486	3.21748
$Qc15$ (MVAr)	1.77177	1.89005	2.52317	1.97585	3.66046	2.22016	1.70649	1.21367	2.43453	4.19032	2.35296	1.66138
$Qc17$ (MVAr)	1.09672	3.06188	2.60997	4.99526	1.63098	2.33127	2.32257	3.22228	2.51590	4.16834	1.82592	2.03201
$Qc20$ (MVAr)	3.35680	4.07665	1.15299	4.73806	3.79895	4.12359	4.03523	4.45266	4.14615	0.93161	3.19843	3.85607
$Qc21$ (MVAr)	4.64387	4.22944	3.70266	4.88739	4.79967	4.54014	3.79062	2.03641	4.84669	3.19365	4.60140	4.99242
$Qc23$ (MVAr)	2.03336	2.33615	3.47532	4.76948	1.57123	3.06564	2.44527	1.10049	3.20386	4.40819	2.38414	2.39577
$Qc24$ (MVAr)	3.55026	4.74509	1.50001	4.99313	4.77354	5.00000	5.00000	1.60649	5.00000	4.40239	3.90612	3.90111
$Qc29$ (MVAr)	0.36652	0.61534	3.28166	1.83736	0.66649	1.63663	0.92889	2.29999	1.92872	1.92074	1.06620	1.26533
Ploss (MW)	1.272131	2.385291	4.018547	5.001507	2.224851	1.447803	1.214170	1.090563	2.360044	3.019415	0.927722	1.174276
VD (p.u.)	0.079769	0.10425	0.237933	0.328735	0.098317	0.103240	0.193152	0.070346	0.150974	0.165084	0.048104	0.082227
Computational Time (Sec)	82.62656	75.39838	108.5183	119.5629	98.60157	93.70196	92.84911	103.8306	92.7024	107.2191	98.26654	97.01964

4) The first problem on EV optimization saw ME-SGO outperform the other algorithms for 5 out of 9 cases for the IEEE30 bus system and 6 out of 9 cases for the IEEE 57 bus system.

5) In the second problem on EV optimization, ME-SGO had the best solutions for 13 scenarios followed by ISOG for 9 scenarios. In this regard, the performance of ME-SGO has been better compared to L-SHADE and

TABLE 52. Tabulation of the best solutions of ORPD (Scenario 13-25) with EV loading for the IEEE 30-bus system.

Decision Variables	Scenario 13	Scenario 14	Scenario 15	Scenario 16	Scenario 17	Scenario 18	Scenario 19	Scenario 20	Scenario 21	Scenario 22	Scenario 23	Scenario 24	Scenario 25
Algorithm with the best Fitness	**ISGO**	**ISGO**	**ISGO**	**ME-SGO**	**ME-SGO**	**L-SHADE**	**ME-SGO**	**ME-SGO**	**ISGO**	**ISGO**	**SMA**	**ISGO**	**ME-SGO**
$V1$ (p.u.)	1.01108	1.04716	1.01784	1.01597	1.01462	1.00667	1.00620	1.02078	1.00549	1.02047	1.02105	1.02222	1.02277
$V2$ (p.u.)	1.01171	1.04527	1.02013	1.01568	1.01413	1.00798	1.01023	1.01951	1.00822	1.01938	1.02156	1.02067	1.01993
$V5$ (p.u.)	0.99425	1.02329	1.00945	1.00236	0.99573	0.99309	1.00315	1.00998	1.00199	1.00606	1.00652	1.00521	1.00237
$V8$ (p.u.)	1.00010	1.02593	1.01024	1.00297	1.00089	0.99772	1.00167	1.00060	0.99757	1.00369	1.01094	1.00826	1.00475
$V11$ (p.u.)	1.02950	1.00571	1.01000	1.00943	1.00622	1.02986	1.01285	1.00997	1.00130	1.01420	0.99814	1.07504	1.00508
$V13$ (p.u.)	1.00944	1.01932	0.98464	1.01316	0.99712	1.01084	0.99997	1.01397	0.99018	1.02961	1.02473	1.01568	1.01466
$T11$ (p.u.)	1.01105	1.04192	1.03239	1.01571	1.02017	1.03050	1.01860	1.01449	0.98214	1.00354	1.00161	1.04412	1.01851
$T12$ (p.u.)	0.98222	0.98081	0.98133	0.96255	0.95257	0.92780	0.95647	0.94600	0.99330	0.98216	0.95748	1.00804	0.94549
$T15$ (p.u.)	1.00838	1.00127	0.97006	1.00251	0.97200	0.97436	0.98553	1.00325	0.97770	0.99733	1.00703	0.99545	0.99843
$T36$ (p.u.)	1.00085	0.99432	0.99045	0.97955	0.98718	0.95382	0.97611	0.98405	0.97985	0.97000	1.00365	0.97068	0.97251
Qc10 (MVAr)	3.81022	4.27715	1.10240	4.64379	0.10427	0.77515	0.62909	0.14268	1.06214	2.24626	2.89596	2.86244	0.40865
Qc12 (MVAr)	1.10000	1.68589	4.53514	3.23311	3.58419	2.15531	3.66962	2.03747	4.07441	2.35277	2.34567	4.53740	1.24638
Qc15 (MVAr)	2.13514	0.64807	4.29994	3.82990	1.40536	2.17645	2.55429	3.23290	2.97133	1.71689	2.54835	1.19948	2.71433
Qc17 (MVAr)	1.40178	1.45448	2.55389	2.65876	0.98555	4.65907	2.86424	3.14120	1.47377	1.65535	2.72846	3.30000	3.26257
Qc20 (MVAr)	1.52463	3.12359	1.50150	4.55005	3.20667	4.12471	3.71616	4.60227	2.46121	2.81622	2.61725	1.36669	4.25684
Qc21 (MVAr)	3.14712	0.69325	1.92586	5.00000	4.59253	2.11047	4.89490	4.93629	2.60137	2.90000	2.84492	2.13975	4.91229
Qc23 (MVAr)	1.92792	0.81469	1.68288	3.22640	1.67712	1.95505	1.72880	3.39927	2.06146	2.89237	2.47846	3.50000	2.56685
Qc24 (MVAr)	3.75965	1.63580	4.32888	4.96871	3.86721	4.94755	4.64516	4.98287	3.67396	2.31164	2.50523	2.38970	4.96260
Qc29 (MVAr)	2.99055	1.88325	0.52745	2.21111	0.57381	0.52516	1.35078	2.29317	1.64097	2.76574	2.64934	1.67409	1.72001
Ploss (MW)	1.755857	2.469085	0.786201	1.828701	1.749486	1.392526	1.021149	2.240514	0.808554	1.650933	1.779429	1.976460	2.225839
VD (p.u.)	0.086189	0.226025	0.105743	0.087598	0.088672	0.100518	0.082698	0.087961	0.053719	0.126303	0.156463	0.156287	0.118801
Computational Time (Sec)	98.529	98.58788	102.620	98.21951	95.97415	145.8494	97.23369	99.66969	102.3035	102.4335	111.313	88.67404	114.7158

TABLE 53. Description of the mathematical model, simulation details and constraints for the optimal dynamic charging problem.

Objective	**Minimization of power deviation from the actual load to the ideal load** $J_1 = min(P_D) = \sum_{t=1}^{T}[P_t - \bar{P}]^2$ where, $t = 1,2,3..T$, are the time intervals, P_D stands for the power deviation, P_t is the toal grid demand with EVs at time t and $\bar{P}$ is the average demand on the grid excluding the EV load	A(24)
	Maximization of owner's degree of satisfaction $J_2 = min(1 - DoS) = 1 - \frac{\sum_{n=1}^{N} SoC_I}{N}$ where, $n = 1,2,3..N$, are the nodes in the power grid, SoC_I stands initial level of SoC.	A(25)
	Combining, we have $J = \alpha.J_1 + (1-\alpha).J_2$ where, α is the weighing factor set to 0.7.	A(26)
Simulation System	**Initial charging time** The initial charging time follows normal distribution and is given by $c(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(r-19)^2}{2}}$ where, r is the rate of charging.	A(27)
	Number of EVs connected for charging At a time instant t, the number of EVs' requiring charging is given by $N_t = N_{EV}^{T}\left[\int_{t}^{t+\Delta t} c(t)dt\right]$ where, N_t is the number of EVs requiring charging at time t, N_{EV}^{T} are the total number of EVs at a given node.	A(28)
Constraints	EV charging power limits are expressed as: $P_{n,min}^{EV} \le P_n^{EV} \le P_{n,max}^{EV}$	A(29)
	Node voltage limits are expressed as: $V_{n,min} \le V_n \le V_{n,max}$	A(30)
	Transformer ratio restraints are expressed as: $\lvert\tau\rvert_{n,min} \le \lvert\tau\rvert_n \le \lvert\tau\rvert_{n,max}$	A(31)
	Branch power transmission constraint is given as: $\lvert P\rvert_l \le \lvert P\rvert_{l,max}$	A(32)
	EV battery energy storage limits are given as: $0.1 \times E_{n,min}^{EV} \le E_n^{EV} \le 0.9 \times E_{n,max}^{EV}$	A(33)

MPEDE which have also integrated the linear population reduction techniques.

6) For the third problem on EV optimization, the performance of ME-SGO L-SHADE and MPEDE were quite competitive with ME-SGO leading for two out of three cases.
7) The fourth problem on EV optimization was a tie between ME-SGO and L-SHADE with both the algorithms leading for 3 cases each.

C. FUTURE SCOPE

ME-SGO can be deployed to a wide spectrum of problems falling under artificial intelligence, power systems, machine learning etc. Practitioners are free to modify the proposed method as per their requirements and hence to encourage such an extendibility, simplicity has been embraced in the design of ME-SGO. The proposed method can be applied to various other optimization areas in power systems and EV optimization. In computer science, the proposed method can

TABLE 54. Description of the mathematical model, simulation details and constraints for the energy efficient control of parallel HEV.

Objective Function	**Minimization of electricity cost and fuel cost** $J = E_c(x) = \sum_{t=1}^{N} \varsigma_\epsilon(t).\Delta t = \sum_{t=1}^{N} \left[\rho_{Fu}\frac{P_E(t)}{3600} + \rho_{El}\frac{P_B(t)}{3600}\right].\Delta t$ A(34) where $\rho_{El} = \alpha_g \frac{\rho_g}{\eta_{B_{ch}}} + (1-\alpha_g)\frac{mean(Fu_{Bc})\rho_{Fu}}{3600\eta_{B_{ch}}\eta_B}$ A(35) $P_B(t) = V_T(t) \times I_B(t)$ A(36) and $V_T(t) = V_{OC}(t) - V_D(t) - I_B(t)R_0$ A(37) $V_D(t) = -\frac{1}{C_d R_d}V_D(t) + \frac{1}{C_d}I_B(t)$ A(38) where, E_c the energy consumption by the HEV, x is the control variable which denotes the power allocation from the vehicular energy management system, ς_ϵ is the cost of the total energy consumption, Δt is the time interval, N denotes the total number of time intervals, ρ_{Fu}, ρ_{El} denote the price of fuel and electricity respectively, $P_E(t)$ and $P_B(t)$ are the engine and battery powers respectively, α_g denotes the proportion of electricity from the grid, ρ_g is the grid electrocute pricing, $\eta_{B_{ch}}$ and η_B are the efficiencies of charging of battery charging and battery pack, Fu_{Bc} is the fuel consumption rate of the engine when charging the battery, V_T is the terminal voltage of the battery pack, I_B is the current of the battery pack, V_{OC} is the open-circuit battery pack voltage, V_D is the diffusion voltage of the battery RC circuit, C_d and R_d denote the capacitance and resistance of the RC network.
Constraints	**Battery power consumption limits** $P_B^{min}(SoC(t)) \leq P_B(t) \leq P_B^{max}(SoC(t))$ A(39) where $SoC(t) = SoC(t_0) - \frac{1}{Q_{nom}}\int_{t_0}^{t} I_B(t)\ dt$ A(40) where, Q_{nom} is the nominal capacity of the battery pack. **Initial Soc** $SoC(t_0) = SoC_0$ A(41) **Engine power limits** $0 \leq P_{Eng}(t) \leq P_{Eng}^{max}$ A(42)

be deployed towards neural networks (NN) training (feed-forward NNs and convolution NNs). Image classification, data classification, pattern recognition etc. can be optimized through the proposed methods. A plan to deploy the current method for the infection detection of COVID-19 from the X-ray images via support vector classifier is in its roots. Feature selection is a potential area of application of the proposed methods through the formulation of a binary version of ME-SGO. The realization of a multi-objective variant is a possibility towards tackling problems requiring a Pareto-optimal front.

APPENDIX

See Figures 2–4 and Tables 27–54.

ACKNOWLEDGMENT

The authors of this article hereby declare the interest and willful consent to publish the article titled "Investigation of a multi-strategy ensemble social group optimization algorithm for the optimization of energy management in electric vehicles" in IEEE Access journal. The authors hereby declare no conflict of interest and would like to thank the encouragement and support of VIT University in the publication of this paper.

REFERENCES

[1] E. Nowicki and C. Smutnicki, "A fast taboo search algorithm for the job shop problem," *Manage. Sci.*, vol. 42, no. 6, pp. 797–813, Jun. 1996.

[2] Z. W. Geem, J. H. Kim, and G. V. Loganathan, "A new heuristic optimization algorithm: Harmony search," *Simulation*, vol. 76, no. 2, pp. 60–68, Feb. 2001, doi: 10.1177/003754970107600201.

[3] E. Atashpaz-Gargari and C. Lucas, "Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition," in *Proc. IEEE Congr. Evol. Comput.*, Sep. 2007, pp. 4661–4667.

[4] R. V. Rao, V. J. Savsani, and D. P. Vakharia, "Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems," *Comput.-Aided Des.*, vol. 43, no. 3, pp. 303–315, Mar. 2011, doi: 10.1016/j.cad.2010.12.015.

[5] P. Niu, S. Niu, N. Liu, and L. Chang, "The defect of the grey wolf optimization algorithm and its verification method," *Knowl.-Based Syst.*, vol. 171, pp. 37–43, May 2019, doi: 10.1016/j.knosys.2019.01.018.

[6] J. K. Cochran, S.-M. Horng, and J. W. Fowler, "A multi-population genetic algorithm to solve multi-objective scheduling problems for parallel machines," *Comput. Oper. Res.*, vol. 30, no. 7, pp. 1087–1102, 2003, doi: 10.1016/S0305-0548(02)00059-X.

[7] H. Wang, Z. Wu, S. Rahnamayan, H. Sun, Y. Liu, and J.-S. Pan, "Multi-strategy ensemble artificial bee colony algorithm," *Inf. Sci.*, vol. 279, pp. 587–603, Sep. 2014, doi: 10.1016/j.ins.2014.04.013.

[8] W. Deng, H. Zhao, L. Zou, G. Li, X. Yang, and D. Wu, "A novel collaborative optimization algorithm in solving complex optimization problems," *Soft Comput.*, vol. 21, no. 15, pp. 4387–4398, Aug. 2017, doi: 10.1007/s00500-016-2071-8.

[9] B. Zhao, C. X. Guo, and Y. J. Cao, "A multiagent-based particle swarm optimization approach for optimal reactive power dispatch," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 1070–1078, May 2005, doi: 10.1109/TPWRS.2005.846064.

[10] W. Du and B. Li, "Multi-strategy ensemble particle swarm optimization for dynamic optimization," *Inf. Sci.*, vol. 178, no. 15, pp. 3096–3109, 2008, doi: 10.1016/j.ins.2008.01.020.

[11] Y. Wang, B. Li, T. Weise, J. Wang, B. Yuan, and Q. Tian, "Self-adaptive learning based particle swarm optimization," *Inf. Sci.*, vol. 181, no. 20, pp. 4515–4538, 2011, doi: 10.1016/j.ins.2010.07.013.

[12] H. Wang, H. Sun, C. Li, S. Rahnamayan, and J. S. Pan, "Diversity enhanced particle swarm optimization with neighborhood search," *Inf. Sci.*, vol. 223, pp. 119–135, Feb. 2013, doi: 10.1016/j.ins.2012.10.012.

[13] Y. Guo, N.-Z. Chen, J. Mou, and B. Zhang, "A quantum-behaved particle swarm optimization algorithm with the flexible single-/multi-population strategy and multi-stage perturbation strategy based on the characteristics of objective function," *Soft Comput.*, vol. 24, no. 9, pp. 6909–6956, May 2020.

[14] B.-Y. Qu, P. N. Suganthan, and J.-J. Liang, "Differential evolution with neighborhood mutation for multimodal optimization," *IEEE Trans. Evol. Comput.*, vol. 16, no. 5, pp. 601–614, Oct. 2012, doi: 10.1109/TEVC.2011.2161873.

[15] G. Wu, R. Mallipeddi, P. N. Suganthanc, R. Wang, and H. Chen, "Differential evolution with multi-population based ensemble of mutation strategies," *Inf. Sci.*, vol. 329, pp. 329–345, Feb. 2016, doi: 10.1016/j.ins.2015.09.009.

[16] G. Wu, X. Shen, H. Li, H. Chen, A. Lin, and P. N. Suganthan, "Ensemble of differential evolution variants," *Inf. Sci.*, vol. 423, pp. 172–186, Jan. 2018, doi: 10.1016/j.ins.2017.09.053.

[17] A. Auger and N. Hansen, "A restart CMA evolution strategy with increasing population size," in *Proc. IEEE Congr. Evol. Comput. (IEEE CEC)*, vol. 2, Sep. 2005, pp. 1769–1776, doi: 10.1109/CEC.2005.1554902.

[18] W. Deng, J. Xu, and H. Zhao, "An improved ant colony optimization algorithm based on hybrid strategies for scheduling problem," *IEEE Access*, vol. 7, pp. 20281–20292, 2019, doi: 10.1109/ACCESS.2019.2897580.

[19] H. Chen, A. A. Heidari, H. Chen, M. Wang, Z. Pan, and A. H. Gandomi, "Multi-population differential evolution-assisted Harris hawks optimization: Framework and case studies," *Future Gener. Comput. Syst.*, vol. 111, pp. 175–198, Oct. 2020, doi: 10.1016/j.future.2020.04.008.

[20] M. Wang and H. Chen, "Chaotic multi-swarm whale optimizer boosted support vector machine for medical diagnosis," *Appl. Soft Comput.*, vol. 88, Mar. 2020, Art. no. 105946, doi: 10.1016/j.asoc.2019.105946.

[21] Q. Tu, X. Chen, and X. Liu, "Multi-strategy ensemble grey wolf optimizer and its application to feature selection," *Appl. Soft Comput.*, vol. 76, pp. 16–30, Mar. 2019, doi: 10.1016/j.asoc.2018.11.047.

[22] A. Naik and S. C. Satapathy, "A comparative study of social group optimization with a few recent optimization algorithms," *Complex Intell. Syst.*, vol. 7, no. 1, pp. 249–295, Feb. 2021, doi: 10.1007/s40747-020-00189-6.

[23] J. J. Jena and S. C. Satapathy, "A new adaptive tuned Social Group Optimization (SGO) algorithm with sigmoid-adaptive inertia weight for solving engineering design problems," *Multimedia Tools Appl.*, 2021, doi: 10.1007/s11042-021-11266-4.

[24] A. Naik, S. C. Satapathy, A. S. Ashour, and N. Dey, "Social group optimization for global optimization of multimodal functions and data clustering problems," *Neural Comput. Appl.*, vol. 30, no. 1, pp. 271–287, Jul. 2018, doi: 10.1007/s00521-016-2686-9.

[25] R. S. M. L. Patibandla and N. Veeranjaneyulu, "Performance analysis of partition and evolutionary clustering methods on various cluster validation criteria," *Arabian J. Sci. Eng.*, vol. 43, no. 8, pp. 4379–4390, Aug. 2018, doi: 10.1007/s13369-017-3036-7.

[26] S. Satapathy and A. Naik, "Social group optimization (SGO): A new population evolutionary optimization technique," *Complex Intell. Syst.*, vol. 2, no. 3, pp. 173–203, 2016, doi: 10.1007/s40747-016-0022-8.

[27] J. Fang, H. Zheng, J. Liu, J. Zhao, Y. Zhang, and K. Wang, "A transformer fault diagnosis model using an optimal hybrid dissolved gas analysis features subset with improved social group optimization-support vector machine classifier," *Energies*, vol. 11, no. 8, pp. 1–18, 2018, doi: 10.3390/en11081922.

[28] Y. Liu, D. Chen, F. Zou, W. Shan, S. Wang, and S. Luo, "Cluster head multi-hop routing algorithm based on improved social group algorithm," in *Proc. 3rd Asia–Pacific Electron. Elect. Eng. Conf. (EEEC)*, Jan. 2019, pp. 31–38, doi: 10.12783/dtetr/eeec2018/26851.

[29] A. Gautam, R. N. Sharma, and V. Kumar, "Short-term hydrothermal scheduling using improved social group optimization algorithm," in *Proc. IEEE 4th Int. Conf. Comput., Power Commun. Technol. (GUCON)*, no. 4, Sep. 2021, pp. 1–5.

[30] A. Naik, S. C. Satapathy, and A. Abraham, "Modified social group optimization—A meta-heuristic algorithm to solve short-term hydrothermal scheduling," *Appl. Soft Comput.*, vol. 95, Oct. 2020, Art. no. 106524, doi: 10.1016/j.asoc.2020.106524.

[31] A. V. S. Swathi, V. V. S. S. Chakravarthy, and M. V. Krishna, "Circular antenna array optimization using modified social group optimization algorithm," *Soft Comput.*, vol. 25, no. 15, pp. 10467–10475, Aug. 2021, doi: 10.1007/s00500-021-05778-2.

[32] V. K. R. A. Kalananda and V. L. N. Komanapalli, "A combinatorial social group whale optimization algorithm for numerical and engineering optimization problems," *Appl. Soft Comput.*, vol. 99, Feb. 2021, Art. no. 106903, doi: 10.1016/j.asoc.2020.106903.

[33] A. K. Singh, A. Kumar, M. Mahmud, M. S. Kaiser, and A. Kishore, "COVID-19 infection detection from chest X-ray images using hybrid social group optimization and support vector classifier," *Cogn. Comput.*, pp. 1–13, Mar. 2021, doi: 10.1007/s12559-021-09848-3.

[34] S. Verma, J. J. Jena, S. C. Satapathy, and M. Rout, "Solving travelling salesman problem using discreet social group optimization," *J. Sci. Ind. Res.*, vol. 79, no. 10, pp. 928–930, 2020.

[35] V. K. R. A. Kalananda and V. L. N. Komanapalli, "A combinatorial social group whale optimization algorithm for numerical and engineering optimization problems," *Appl. Soft Comput.*, vol. 99, Feb. 2021, Art. no. 106903, doi: 10.1016/j.asoc.2020.106903.

[36] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[37] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, Feb. 2016, doi: 10.1016/j.advengsoft.2016.01.008.

[38] S. Li, H. Chen, M. Wang, A. A. Heidari, and S. Mirjalili, "Slime mould algorithm: A new method for stochastic optimization," *Future Gener. Comput. Syst.*, vol. 111, pp. 300–323, Oct. 2020, doi: 10.1016/j.future.2020.03.055.

[39] M. Khishe and M. R. Mosavi, "Chimp optimization algorithm," *Expert Syst. Appl.*, vol. 149, Jul. 2020, Art. no. 113338, doi: 10.1016/j.eswa.2020.113338.

[40] J. J. Liang, A. K. Qin, P. N. Suganthan, and S. Baskar, "Comprehensive learning particle swarm optimizer for global optimization of multimodal functions," *IEEE Trans. Evol. Comput.*, vol. 10, no. 3, pp. 281–295, Jun. 2006, doi: 10.1109/TEVC.2005.857610.

[41] G. Zhu and S. Kwong, "Gbest-guided artificial bee colony algorithm for numerical function optimization," *Appl. Math. Comput.*, vol. 217, pp. 3166–3173, Dec. 2010, doi: 10.1016/j.amc.2010.08.049.

[42] R. Tanabe and A. S. Fukunaga, "Improving the search performance of SHADE using linear population size reduction," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2014, pp. 1658–1665, doi: 10.1109/CEC.2014.6900380.

[43] K. V. Price, N. H. Awad, M. Z. Ali, and P. N. Suganthan. (Nov. 2018). *Problem Definitions and Evaluation Criteria for the 100-Digit Challenge Special Session and Competition on Single Objective Numerical Optimization*. [Online]. Available: http://www.ntu.edu.sg/home/EPNSugan/index_files/CEC2019

[44] J. Brest, M. S. Maucec, and B. Boskovic, "The 100-digit challenge: Algorithm jDE100," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 19–26, doi: 10.1109/CEC.2019.8789904.

[45] F. Lezama, J. Soares, R. Faia, and Z. Vale, "Hybrid-adaptive differential evolution with decay function (HyDE-DF) applied to the 100-digit challenge competition on single objective numerical optimization," in *Proc. Genet. Evol. Comput. Conf. Companion*, Jul. 2019, pp. 7–8, doi: 10.1145/3319619.3326747.

[46] S. X. Zhang, W. S. Chan, K. S. Tang, and S. Y. Zheng, "Restart based collective information powered differential evolution for solving the 100-digit challenge on single objective numerical optimization," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 14–18, doi: 10.1109/CEC.2019.8790279.

[47] A. Viktorin, R. Senkerik, M. Pluhacek, T. Kadavy, and A. Zamuda, "DISH algorithm solving the CEC 2019 100-digit challenge," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 1–6, doi: 10.1109/CEC.2019.8789936.

[48] A. Epstein, M. Ergezer, I. Marshall, and W. Shue, "GADE with fitness-based opposition and tidal mutation for solving IEEE CEC2019 100-digit challenge," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 395–402, doi: 10.1109/CEC.2019.8790159.

[49] J. Lu, X. Zhou, Y. Ma, M. Wang, J. Wan, and W. Wang, "A novel artificial bee colony algorithm with division of labor for solving CEC 2019 100-digit challenge benchmark problems," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 387–394, doi: 10.1109/CEC.2019.8790252.

[50] D. Molina and F. Herrera, "Applying memetic algorithm with improved L-SHADE and local search pool for the 100-digit challenge on single objective numerical optimization," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 7–13, doi: 10.1109/CEC.2019.8789916.

[51] T. Kadavy, M. Pluhacek, R. Senkerik, and A. Viktorin, "The ensemble of strategies and perturbation parameter in self-organizing migrating algorithm solving CEC 2019 100-digit challenge," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 372–375, doi: 10.1109/CEC.2019.8790012.

[52] P. P. Biswas, P. N. Suganthan, R. Mallipeddi, and G. A. J. Amaratunga, "Optimal power flow solutions using differential evolution algorithm integrated with effective constraint handling techniques," *Eng. Appl. Artif. Intell.*, vol. 68, pp. 81–100, Feb. 2018, doi: 10.1016/j.engappai.2017.10.019.

[53] S. K. Injeti and V. K. Thunuguntla, "Optimal integration of DGs into radial distribution network in the presence of plug-in electric vehicles to minimize daily active power losses and to improve the voltage profile of the system using bio-inspired optimization algorithms," *Protection Control Mod. Power Syst.*, vol. 5, no. 1, pp. 1–15, Dec. 2020, doi: 10.1186/s41601-019-0149-x.

[54] P. P. Biswas, P. N. Suganthan, R. Mallipeddi, and G. A. J. Amaratunga, "Optimal reactive power dispatch with uncertainties in load demand and renewable energy sources adopting scenario-based approach," *Appl. Soft Comput.*, vol. 75, pp. 616–632, Feb. 2019, doi: 10.1016/j.asoc.2018.11.042.

[55] J. Yang, L. He, and S. Fu, "An improved PSO-based charging strategy of electric vehicles in electrical distribution grid," *Appl. Energy*, vol. 128, no. 3, pp. 82–92, Sep. 2014, doi: 10.1016/j.apenergy.2014.04.047.

[56] Z. Chen, R. Xiong, and J. Cao, "Particle swarm optimization-based optimal power management of plug-in hybrid electric vehicles considering uncertain driving conditions," *Appl. Energy*, vol. 96, pp. 197–208, Feb. 2016, doi: 10.1016/j.energy.2015.12.071.

[57] X. Wu, B. Cao, X. Li, J. Xu, and X. Ren, "Component sizing optimization of plug-in hybrid electric vehicles," *Appl. Energy*, vol. 88, no. 3, pp. 799–804, Mar. 2011, doi: 10.1016/j.apenergy.2010.08.018.

[58] Z. Liu, F. Wen, and G. Ledwich, "Optimal siting and sizing of distributed generators in distribution systems considering uncertainties," *IEEE Trans. Power Del.*, vol. 26, no. 4, pp. 2541–2551, Oct. 2011, doi: 10.1109/TPWRD.2011.2165972.

[59] J. Zhao, F. Wen, Z. Y. Dong, Y. Xue, and K. P. Wong, "Optimal dispatch of electric vehicles and wind power using enhanced particle swarm optimization," *IEEE Trans. Ind. Informat.*, vol. 8, no. 4, pp. 889–899, Nov. 2012, doi: 10.1109/TII.2012.2205398.

[60] J. P. Trovão, P. G. Pereirinha, H. M. Jorge, and C. H. Antunes, "A multi-level energy management system for multi-source electric vehicles—An integrated rule-based meta-heuristic approach," *Appl. Energy*, vol. 105, pp. 304–318, May 2013, doi: 10.1016/j.apenergy.2012.12.081.

[61] J. Zheng, X. Wang, K. Men, C. Zhu, and S. Zhu, "Aggregation model-based optimization for electric vehicle charging strategy," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 1058–1066, Jun. 2013, doi: 10.1109/TSG.2013.2242207.

[62] J. Shen, S. Dusmez, and A. Khaligh, "Optimization of sizing and battery cycle life in battery/ultracapacitor hybrid energy storage systems for electric vehicle applications," *IEEE Trans. Ind. Informat.*, vol. 10, no. 4, pp. 2112–2121, Nov. 2014, doi: 10.1109/TII.2014.2334233.

[63] J. Tan and L. Wang, "Integration of plug-in hybrid electric vehicles into residential distribution grid based on two-layer intelligent optimization," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1774–1784, Jul. 2014, doi: 10.1109/TSG.2014.2313617.

[64] D. Goeke and M. Schneider, "Routing a mixed fleet of electric and conventional vehicles," *Eur. J. Oper. Res.*, vol. 245, no. 1, pp. 81–99, Aug. 2015, doi: 10.1016/j.ejor.2015.01.049.

[65] H. Yang, S. Yang, Y. Xu, E. Cao, M. Lai, and Z. Dong, "Electric vehicle route optimization considering time-of-use electricity price by learnable Partheno-genetic algorithm," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 657–666, Mar. 2015, doi: 10.1109/TSG.2014.2382684.

[66] M. Keskin and B. Çatay, "Partial recharge strategies for the electric vehicle routing problem with time windows," *Transp. Res. C, Emerg. Technol.*, vol. 65, pp. 111–127, Apr. 2016, doi: 10.1016/j.trc.2016.01.013.

[67] Q. Kang, J. Wang, M. Zhou, and A. C. Ammari, "Centralized charging strategy and scheduling algorithm for electric vehicles under a battery swapping scenario," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 3, pp. 659–669, Mar. 2016, doi: 10.1109/TITS.2015.2487323.

[68] S. Suganya, S. C. Raja, and P. Venkatesh, "Simultaneous coordination of distinct plug-in hybrid electric vehicle charging stations: A modified particle swarm optimization approach," *Energy*, vol. 138, pp. 92–102, Nov. 2017, doi: 10.1016/j.energy.2017.07.036.

[69] A. Awasthi, K. Venkitusamy, S. Padmanaban, R. Selvamuthukumaran, F. Blaabjerg, and A. K. Singh, "Optimal planning of electric vehicle charging station at the distribution system using hybrid optimization algorithm," *Energy*, vol. 133, pp. 70–78, Aug. 2017, doi: 10.1016/j.energy.2017.05.094.

[70] H. Wu, G. K.-H. Pang, K. L. Choy, and H. Y. Lam, "Dynamic resource allocation for parking lot electric vehicle recharging using heuristic fuzzy particle swarm optimization algorithm," *Appl. Soft Comput.*, vol. 71, pp. 538–552, Oct. 2018, doi: 10.1016/j.asoc.2018.07.008.

[71] W. Zhao, Z. Luan, and C. Wang, "Parametric optimization of novel electric–hydraulic hybrid steering system based on a shuffled particle swarm optimization algorithm," *J. Cleaner Prod.*, vol. 186, pp. 865–876, Jun. 2018, doi: 10.1016/j.jclepro.2018.03.180.

[72] T. Zhu, H. Zheng, and Z. Ma, "A chaotic particle swarm optimization algorithm for solving optimal power system problem of electric vehicle," *Adv. Mech. Eng.*, vol. 11, no. 3, pp. 1–9, 2019, doi: 10.1177/1687814019833500.

[73] H. Zhang, L. Tang, C. Yang, and S. Lan, "Locating electric vehicle charging stations with service capacity using the improved whale optimization algorithm," *Adv. Eng. Informat.*, vol. 41, Aug. 2019, Art. no. 100901, doi: 10.1016/j.aei.2019.02.006.

[74] Y. Li, B. Zhu, N. Zhang, H. Peng, and Y. Chen, "Parameters optimization of two-speed powertrain of electric vehicle based on genetic algorithm," *Adv. Mech. Eng.*, vol. 12, no. 1, pp. 1–16, 2020, doi: 10.1177/1687814020901652.

[75] C. A. Folkestad, N. Hansen, K. Fagerholt, H. Andersson, and G. Pantuso, "Optimal charging and repositioning of electric vehicles in a free-floating carsharing system," *Comput. Oper. Res.*, vol. 113, Jan. 2020, Art. no. 104771, doi: 10.1016/j.cor.2019.104771.

[76] Y.-H. Jia, Y. Mei, and M. Zhang, "A bilevel ant colony optimization algorithm for capacitated electric vehicle routing problem," *IEEE Trans. Cybern.*, early access, Apr. 20, 2021, doi: 10.1109/TCYB.2021.3069942.

[77] S. Das, P. Saha, S. C. Satapathy, and J. J. Jena, "Social group optimization algorithm for civil engineering structural health monitoring," *Eng. Optim.*, vol. 53, no. 10, pp. 1651–1670, Oct. 2021, doi: 10.1080/0305215X.2020.1808974.

[78] C. V. Camp and M. Farshchin, "Design of space trusses using modified teaching–learning based optimization," *Eng. Struct.*, vols. 62–63, pp. 87–97, Mar. 2014, doi: 10.1016/j.engstruct.2014.01.020.

AALA KALANANDA VAMSI KRISHNA REDDY received the B.Tech. degree in electrical and electronics engineering from Jawaharlal Nehru Technological University, Ananthapur, India, in 2017, and the M.Tech. degree in electrical engineering from Lovely Professional University, Phagwara, India, in 2019. He is currently pursuing the Ph.D. degree with the School of Electrical Engineering, Vellore Institute of Technology, Vellore, India.

His research interests include swarm and evolutionary computation, electric vehicles, and power systems.

KOMANAPALLI VENKATA LAKSHMI NARAYANA (Senior Member, IEEE) received the B.Tech. degree in electronics and instrumentation engineering from Nagarjuna University, Guntur, India, in 2001, the M.Tech. degree in electrical engineering from the Motilal Nehru National Institute of Technology (MNNIT), Allahabad, India, in 2006, and the Ph.D. degree in instrumentation engineering from Andhra University, Visakhapatnam, in 2013.

He has 18 years of experience in both teaching and research. He is currently a Senior Associate Professor with the School of Electrical Engineering, Vellore Institute of Technology, Vellore, India. As a published researcher, he has authored or coauthored over 50 research papers (five papers in IEEE Sensors Journals and six more in other SCI journals) and published in various peer-reviewed journals, book chapters, and conferences of international repute. He has reviewed a good number of research papers of *IET Science, Measurement and Technology*, IEEE Access, *Artificial Intelligence Review*, *Journal of Engineering Science and Technology* (JESTEC), and *Recent Advances in Electrical and Electronic Engineering*. His research interests include sensors and signal conditioning, measurements, wireless sensor networks, optimization, process instrumentation, and virtual instrumentation. He is also the recipient of the Gold Medal Award, 2016 for his outstanding academic performance in M.Tech. Program at MNNIT.