IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 21 December 2023, accepted 5 January 2024, date of publication 9 January 2024, date of current version 17 January 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3351710

RESEARCH ARTICLE

Multi-Objective Security Constrained Unit Commitment via Hybrid Evolutionary Algorithms

AAMIR ALI[1], ARSLAN SHAH[1], MUHAMMAD USMAN KEERIO[1], NOOR HUSSAIN MUGHERI[1], GHULAM ABBAS[2], EZZEDDINE TOUTI[3], MOHAMMED HATATAH[4], AMR YOUSEF[5,6], AND MOUNIR BOUZGUENDA[7]

[1]Department of Electrical Engineering, Quaid-e-Awam University of Engineering Science and Technology, Nawabshah, Sindh 67450, Pakistan
[2]School of Electrical Engineering, Southeast University, Nanjing 210096, China
[3]Department of Electrical Engineering, College of Engineering, Northern Border University, Arar, Saudi Arabia
[4]Department of Electrical Engineering, Al-Baha University, Alaqiq 65779, Saudi Arabia
[5]Department of Electrical Engineering, College of Engineering, University of Business and Technology, Jeddah 21589, Saudi Arabia
[6]Engineering Mathematics Department, Faculty of Engineering, Alexandria University, Alexandria 21544, Egypt
[7]Department of Electrical Engineering, King Faisal University, Al-Ahsa 31982, Saudi Arabia

Corresponding author: Ezzeddine Touti (esseddine.touti@nbu.edu.sa)

The authors extend their appreciation to the Deanship of Scientific Research at Northern Border University, Arar, KSA for funding this research work through the project number "NBU-FFR-2024-2448-02."

ABSTRACT This paper addresses the challenging problem of Unit Commitment (UC), which involves the optimal scheduling of power generation units while adhering to numerous network operational constraints called security-constrained UC (SCUC). SCUC problem aims to minimize costs subject to turning on economically efficient generators and turning off expensive ones. These operational constraints include load balancing, voltage level at buses, minimum up and down time requirements, spinning reserve, and ramp up and down constraints. The SCUC problem, subject to these operational constraints, is a complex mixed-integer nonlinear problem (MINLP). There has been a growing interest in using evolutionary algorithms (EAs) to tackle large-scale multi-objective MINLP problems in recent two decades. This paper introduces a novel approach to address the SCUC problem, which is further complicated by including network constraints. They are pioneering the integration of single and multi-objective EAs to solve the SCUC problem while incorporating AC network constraints through hybrid binary and real coded operators. The development of an ensemble algorithm that combines mixed real and binary coded operators, extended by a bidirectional coevolutionary algorithm to tackle multi-objective SCUC problems. The paper implements a new formulation based on three conflicting objective functions: cost of energy supplied, startup and shutdown costs of generators, energy loss, and voltage deviation to solve the SCUC problem. Implementing a new formulation also addresses the solution of single and multi-objective SCUC problems using a combination of proposed technical and economic objective functions. The proposed algorithm is rigorously tested on a 10-unit IEEE RTS system and a 6-unit IEEE 30-bus test system, both with and without security constraints, addressing week-ahead and day-ahead SCUC scenarios. Simulation results show that the proposed algorithm finds near-global optimal solutions compared to other state-of-the-art EAs. Additionally, the research demonstrates the effectiveness of the proposed search operator by integrating it with a multi-objective coevolutionary algorithm driven by both feasible and infeasible solutions, showcasing superior performance in solving multi-objective SCUC problems. These results are compared with various recently implemented Multi-Objective Evolutionary Algorithms (MOEAs), demonstrating the superiority of

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

© 2024 The Authors. This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 License.
For more information, see https://creativecommons.org/licenses/by-nc-nd/4.0/

the proposed algorithm in terms of convergence and diversity. A comparison of simulation results demonstrates that the proposed algorithm finds better convergence and diversity than state-of-the-art MOEAs.

INDEX TERMS Security constrained unit commitment, evolutionary algorithms, optimal power flow, constraint handling techniques, multi-objective optimization.

NOMENCLATURE

Abbreviations

UC	Unit Commitment.
SCUC	Security Constrained Unit Commitment.
MILP	Mixed Integer Linear Problem.
MINLP	Mixed Integer Nonlinear Problem.
OPF	Optimal Power Flow.
RTS	Reliability Test System.
EAs	Evolutionary Algorithms.
DE	Differential Evolution.
MOEAs	Multi-objective Evolutionary Algorithms.
ANN	Artificial Neural network.
LR	Lagrangian Relaxation.
BiCo	Bi-directional Co-evolution.
GA	Genetic Algorithm.
NSGAII	Nondominated Sorting Genetic Algorithms.
SVC	Shunt Var Compensator.
AD	Angle-based Density.
CV	Constraint Violation.
VD	Voltage Deviation.
CEL	Cost of Energy loss.
PF	Pareto Front.
PS	Pareto Set.
HVI	Hyper Volume Indicator.
BCS	Best Compromise Solution.
FR	Feasibility Ratio.
CDP	Constraint Domination Principle

Indices/ Variables/ Parameters

T_n	Span length of time.
N_G	Total number of generators.
N_τ	Total number of transformers.
N_C	Total number of SVC.
nl	Total Number of Transmission lines.
a_i, b_i, c_i	Cost parameters of thermal generators.
P_D^t, Q_D^t	Total active and reactive load demand at time t.
P_i^{max}, P_i^{min}	Rated maximum and minimum of generator i.
$R(t)$	System spinning reserve requirement at hour t.

Indices/ Variables/ Parameters

f_1	Cost of active power generation and Startup cost.
f_2	Cost of Energy loss.
f_3	Voltage Deviation.
$C(P_g)$	Total operating cost of thermal generators.
P_{gi}^t	Active power generation of unit i at time t.
SU_i	The start-up Cost of ith thermal generator.
SD_i	Shut Down cost of ith thermal generator.
P_{G_i} and Q_{G_i}	Actual active and reactive power injection of ith unit.
$F_i(P_i(t))$	Quadratic Cost of ith Thermal Generators.
P_D and Q_D	Active and reactive power demand.
V_{G_i}	The voltage set point of ith generator.
P_{loss}, Q_{loss}	Active and Reactive Power Loss.
a, b, c	Thermal generator Cost parameters.
$S_i(v_i(t))$	Startup cost.
$S_i(w_i(t))$	Shut-down cost.
UR_i	Ramp up rate.
DR_i	Ramp down rate.
UH_i	Ramp up.
τ_j	transformer tap setting.
$C_i(t)$	Constrained generating capability of unit i at hour t.
$F_i(P_i^t)$	Cost of i^{th} at output power P_i^t at current time t.
$t = 1, \ldots, T_n$	Total number of hours.
$i = 1, \ldots, N_g$	Total number of generators.
V_L	Load Bus voltage.
N_L	Number of Load buses.
$u_i(t)$	Binary decision vector of generator i at hour t, 1 if unit is online and 0 elsewhere.
t_{up} and t_{down}	Minimum up and down time.
UR_i and DR_i	Ramp up and down limits.
$\boldsymbol{x}$	Decision vector.
$h(\boldsymbol{x})$	Equality constraint Function.
$g(\boldsymbol{x})$	Inequality constraint Function.
δ_{mn}	Voltage angle difference of branch between bus m and n.
$G_{q(mn)}$	the transfer conductance of branch (line) q connecting buses m and n.
$v_i(t)$ and $w_i(t)$	Binary startup and shut down states of generator i at time t, 1 if unit is start up or shut down at time t, 0 elsewhere.
S_{l_q}	Actual MVA branch flow limit.

I. INTRODUCTION

The unit commitment problem (UC) involves determining the optimal startup and shut down schedules of thermal generators and the economic dispatch of the online generators to meet the forecasted demand over a specific short-term time period (e.g., 24 hours). The UC problem is one of the most important problems in power system operation. The UC problem is a day-ahead scheduling problem and comprises of two tasks: one is determining the on/off status of the thermal units; the other is the optimal power flow (OPF) which requires distributing the system load demand to the committed thermal units [1]. The various past to recent survey papers [2], [3], [4], [5], [6] describe that the UC is a complex np-hard, non-convex, mixed-integer nonlinear problem where the cost of generators is minimized to obtain the best schedule of units. Optimizing electricity generation provides numerous benefits to market participants and end users [7]. As a result of the problem's magnitude and computational constraints, nevertheless, it is not a simple task. Due to this, numerous works in literature suggest various methods for resolving this issue in the best possible way, making them a crucial area for operational research advancements. To correctly operate the generators and reduce costs, UC must decide which generators to turn on and which to turn off based on variation in load demand and subject to satisfy various operational constraints [8], [9], [10] and the committed units must also be economically dispatched [11]. The computational time complexity of the UC problem increases exponentially as the size of a network is increased [12]. The biggest expense associated with the unit commitment problem is fuel usage () [13]. The authors in [5] highlights the significance of accurately representing these costs by noting that a utility would gain annually millions of euros from a 0.5% fuel savings in electricity generation.

To maximize profitability [5], [9], research is concentrated on refining the modeling detail. In previous decades, the thermal foundation of power systems was often provided by coal plants. Fast-ramping gas turbines were employed to meet demand peaks whereas combined cycles gas turbines were reserved for times of high demand [14]. Since this organization was stable throughout time, effective asset management did not necessitate significant modeling advancements. In power system generation scheduling, two duties are taken into account. One of these is the unit commitment, which establishes the unit's start-up and shutdown schedules to reduce system fuel consumption. The other is economic dispatch, which allows system load demands to committed generating units to reduce the cost of power generation [15]. The economic operation is noteworthy since a small decrease in fuel cost as a percentage results in significant system operation cost savings [16]. The UC dilemma typically encompasses both of these decisions because they are related. Finding the overall least expensive way to run the power system over the scheduling horizon is the goal. Recently, many studies comprised of various single and multi-objective based on numerical, metaheuristic and hybrid combination of evolutionary and classical algorithms have been successfully applied to find the optimal solution of UC problem. Classical Mixed integer Linear programming (MILP) based on Quadratic programming given [17] and linear programming [18], [19], are the single objective optimization techniques which are used to minimize the cost subject to satisfy various constraints. These techniques usually approximate the nonlinear objective functions or constraints.

The AI techniques have combined practical operational strategies with mathematical techniques to progress the system models significantly. The mechanism of ANN mimics the learning process of the human brain has been discussed in [5]. It has been proposed in several studies looking at the unit commitment problem that the unit's generating capability changes in steps from zero to the rated capacity and vice versa [20] and startup and shutdown costs proposed in [21], to avoid brittle failure of before online of the unit. Further, most of the authors in the literature consider unit step function to satisfy physical constraints during online units such as ramp up and ramp down [22]. All activities are started as soon as the unit reaches its rated capacity when employing a step function to reflect changes in generating capability, which indicates an unrealistic treatment of energy, especially when the unit start-up is a lengthy process [23]. Similar to how it takes time for the turbine to cool down when a unit is shutting down, so does it. Contrary to the scenario where the changes in unit-producing capacity are treated as a step function, the remaining energy is to be utilized to meet the load demand before the unit-generating capability declines to its lower limit [24]. Ramping up was once thought of as a dynamic dispatch in the economic dispatch. A dynamic procedure was carried out together with the economic dispatch to satisfy the ramping limits [25]. Dynamic programming (DP) is considered to handle these ramping constraints in the economic dispatch sub-problem of the UC problem. DP-based algorithms are time-consuming, therefore, this study avoids DP to implement for the solution of generation scheduling [26]. In [27], a feasible and near-optimal solution to the UC problem is obtained by relaxing the ramping constraints and using step functions—in this function online generator can inject 100% of its capacity—to express the generating capabilities. After that, GA is implemented to generate possible scheduling, and a heuristic method is applied to solve UC. In [28], genetic algorithm were used to solve the UC problem. In recent years, researchers have shown interest and have looked for more effective ways to approach the UC problem. However, the non-convex UC problem has convergence issues when using classical Lagrange relaxation (LR) approach [29]. These are gradient-based and experience a significant bottleneck when they hit local minima [9]. In general, the UC problem is formulated as a nonconvex MINLP, and the scale of this problem creates challenges to solving large UC problems [30], [31]. The dramatic increase in the efficiency of MINLP solvers has encouraged the thorough exploitation of their capabilities [32].

Linear approximation methods often simplify the unit commitment problem by linearizing the cost functions, which can lead to inaccurate results, especially in systems with nonlinear cost functions. This oversimplification may not account for the complexities and nuances of real-world power systems. Many unit commitment problems involve nonlinear constraints, such as ramp rate limits, minimum up and down times, and prohibited operating zones. Linear approximation methods struggle to handle these nonlinear constraints effectively, leading to suboptimal solutions. Linear approximations may not capture the true operating characteristics of generating units accurately. This lack of accuracy can lead to suboptimal schedules, increased operating costs, and potential violations of system constraints. Recently, various single objective evolutionary algorithms (EAs) have been implemented to find the solution of UC problem these includes particle swarm optimization (PSO) [33], Coyote Optimization Algorithm (COA) [34], Binary African Vultures Optimization Algorithm (BAVOA) [10], monarch butterfly optimization (MBO) [9], Gradient Based Optimizer (GBO) [35], Binaryfish migration optimization [36], binary particle swarm optimization (BPSO) [37], improved PSO [38] and weighted improved crazy PSO (WICPSO) [39].

Single-objective EOAs typically aim to find a single optimal solution based on a specific objective function, such as minimizing generation costs, emission rate, profit maximization etc. However, the UCP often involves multiple conflicting objectives, including cost minimization, reliability, and environmental impact. Single objective EAs explore the solution space through a population of individuals, and they may not guarantee the exploration of the entire solution space. This limitation can result in the algorithm getting stuck in local optima, missing global optimal solutions, and producing suboptimal schedules. Moreover, computational effort can be challenging for large-scale UC problems with many generating units and constraints. UC problems involves a variety of complex constraints, such as ramp rate limits, minimum up and down times, and prohibited operating zones. Single-objective EAs may struggle to handle these constraints effectively, leading to solutions that violate technical or operational constraints. Furthermore, UC problem involves a variety of complex constraints, such as ramp rate limits, minimum up and down times, and prohibited operating zones. Single-objective EAs may struggle to handle these constraints effectively, leading to solutions that violate technical or operational limits. As mentioned earlier, UC problem often involves multiple conflicting objective functions. Single-objective EAs cannot simultaneously optimize multiple objectives, which limits their ability to explore trade-offs between objectives effectively.

Multi-objective evolutionary algorithms (MOEAs), on the other hand, are specifically designed to address the limitations of single objective EAs. They can simultaneously optimize multiple objectives, identify a set of Pareto-optimal solutions that represent trade-offs, and provide a more balanced and comprehensive approach to solving UC problems. As a result, in last two decades MOEAs attain increasingly favored to solve complex, multi-objective optimization problems like UC. In the literature, various MOEAs based techniques were implemented to solve UC problem. These includes: nondominated soring genetic algorithm (NSGAII) [40], multi-objective EA based on decomposition with the binary variables are searched by GA search operators (MOEA/D-GA) [41], multi-objective two-stage compromise programming (CP) [42], multi-objective based-on mixed-integer linear programming (MILP) [43] and Multi-Objective Evolutionary Policy Search (MEPS) [44]. In the multi-objective UC (MOUC) problem mostly cost based, profit based, emission reduction based, and voltage stability index based objective functions are considered to find the optimal solution of UC problem. In the context of recent literature, it is evident that the simultaneous consideration of combined technical and economical objective functions in solving the multi-objective unit commitment (MOUC) problem has been largely overlooked. As a result, this paper introduces a novel formulation that integrates both economic and technical objective functions to address the MOUC problem effectively. Moreover, IEEE 11units reliability test network and IEEE 6 units 30-bus test networks are adopted to solve extensive case studies. Their comparison and analysis are presented to demonstrate the effectiveness of the proposed hybrid strategy to solve unit commitment of conventional thermal generators. In the proposed formulation, UC decision variables and generation scheduling variables are simultaneously obtained and applied to solve security constrained multi-objective UC problem. During optimization, step length binary decision variable is obtained by using crossover and mutation operators of binary GA, whereas continuous decision variables are searched using crossover and mutation operators of real coded GA.

The SCUC problem is a challenging mixed-integer nonlinear problem (MINLP) made even more complex by the presence of operational AC power flow constraints. Traditional optimization techniques struggle to find optimal solutions for such intricate problems. In response, this paper employs a hybrid Genetic Algorithm (GA) approach based on MINLP methodology to tackle the SCUC problem. For the multi-objective SCUC problem, bidirectional coevolution (BiCo) based MOEA hybridized with the newly introduced variation operators to optimize both single, bi and tri-objective functions. In the proposed algorithm, a straightforward binary encoding process is adopted, where binary variables (u, v, and w in this paper) are encoded as binary strings. If there are N_g units and T_n scheduling periods in hours, each unit is either ON state (indicated by '1') or OFF (indicated by '0') at each hour. Concatenating these binary strings for all N_g units result in an $N_g - T_n$ bit string. Furthermore, multi-objective SCUC problem is solved through a two-step process. First, binary coding is used to determine UC decision variables, ensuring compliance with constraints such as minimum up and down times, spinning reserves, and security constraints. In the second step, a wide range of nondominated solutions are obtained. Before evaluating the objective functions, all the constraints of SCUC problem must be addressed. Once all constraints are satisfied, the total operating cost, startup cost, cost of energy loss, and voltage deviation (VD) objective functions are computed. This approach ultimately yields an economically optimal unit commitment schedule that adheres to system operating constraints. This paper has the following four important contributions, which are summarized as;

1. A new formulation is implemented to find the solution of single and multi-objective SCUC problem based on technical and economical objective functions. This is the First attempt to propose a single and multi-objective EAs to solve SCUC problem along with AC network constraints.
2. Efficiently solve the SCUC problem considering network-based AC power flow constraints considering technical and economical single, bi and tri objective functions.
3. An ensemble algorithm based on integration of hybrid real and binary coded operators' strategy is developed and extended with bidirectional coevolutionary algorithm to solve Multi-objective SCUC problem.
4. Week ahead and day ahead SCUC problems are solved on 11-unit IEEE RTS system and 6-unit IEEE 30-bus test systems with and without security constraints. Simulation results of proposed single and multi-objective EAs have been compared and analyzed with the recently implemented EAs and MOEAs.

The rest of this article is divided into the following sections. The SCUC Problem formulation is provided in Section II. In section III, specifics the proposed methodology. Section IV presents proposed study cases and simulation results. Section V brings the conclusion.

II. MATHEMATICAL PROBLEM FORMULATION

A. OBJECTIVE FUNCTIONS

In this paper, solution of multi-objective SCUC problem is obtained by considering both technical and economic objective functions. In the Proposed techno-economic multi-objective SCUC problem formulation involves a delicate balance between minimization of operation cost, cost of energy loss, and maximizing voltage stability index. Therefore, in this paper, economical objective functions such as operation cost of thermal generators along with the startup cost and cost of energy loss and one technical objective functions such as voltage deviation are considered to find the solution of single and multi-objective SCUC problem.

1) TOTAL OPERATING COST (f_1)

The generation scheduling challenge seeks to reduce the overall cost of system operation while adhering to the system operating limits. This objective function comprises the fuel cost for producing electricity as well as the start-up and shut-down costs of thermal generators. The total operating cost of the UC problem can be given as:

$$f_1 = C(P_g) = \sum_{t=1}^{T_n} \sum_{i=1}^{N_g} [F_i(P_i(t)) \times u_i(t) + SU_i(v_i(t)) + SD_i(w_i(t))] \tag{1}$$

whereas the Fuel cost of generator i at time t can be computed as;

$$F_i(P_i(t)) = a_i + b_i * P_i + c_i * P_i^2 \tag{2}$$

Additionally, a significant amount of energy must be used to bring the thermal unit online because the temperature and pressure of the unit must be moved slowly. As a result of the commitment and de-commitment status, this energy enters the unit commitment problem as a start-up cost $SU_i(v_i(t))$ but does not result in any MW integration in the system unit. Suppose the status of unit i at $u_i(t-1)$ is OFF and it becomes ON in the next hour at $u_i(t)$, then startup cost $SU_i(v_i(t))$ is applied and it depends upon the number of hours that unit i has been recommitted. Shut down cost $SD_i(w_i(t))$ is active if the status of unit $u_i(t-1)$ is ON at time $t-1$ and becomes off in the next period $u_i(t)$. In the literature [1], most researchers neglect the shutdown cost because it is often modeled as a constant cost parameter in the thermal generators or its value is small compared to startup cost; therefore, in this paper shut-down cost is also neglected during de-commitment.

2) COST OF ENERGY LOSS (f_2)

Due to inherent resistance of the transmission system, the real power loss is unavoidable. The real power loss (in MW) in a transmission line is expressed as:

$$P_{loss} = \sum_{q=1}^{nl} G_{q(mn)} \left[V_m^2 + V_n^2 - 2V_m V_n \cos(\delta_{mn})\right] \tag{3}$$

where $\delta_{mn} = \delta_m - \delta_n$ is the voltage angle difference of buses m and n. $G_{q(mn)}$ signifies the transfer conductance of branch (line) q connecting buses m and n. nl shows the total number of transmission lines. Second objective function is minimization of total cost of energy loss in the entire time horizon, and it is computed as

$$f_2 = C(P_{loss}) = \text{a} \times \sum_{t=1}^{N_t} P_{loss}^t \tag{4}$$

where, P_{loss}^t power loss of the network at time t slot and 'a' is the cost loss co-efficient equal to 0.01\$/MWh.

3) NETWORK VOLTAGE DEVIATION (f_3)

Voltage deviation (VD) is a measure of voltage quality in the network. The index of deviation is also important from security aspect. The indicator is formulated as cumulative deviation of voltages of all load buses (PQ buses) in the network from nominal value of unity. Mathematically, VD in the entire time horizon is computed as;

$$f_3 = VD = \sum_{t=1}^{T_n} \left(\sum_{p=1}^{N_L} \left| V_{L_p}^t - 1 \right| \right) \tag{5}$$

N_L shows number of load buses, V_{Lp} is the load bus voltage.

B. CONSTRAINTS

The constraints for the unit commitment problem are:

1) OPF NETWORK CONSTRAINTS

During optimization all the optimal power flow (OPF) constraints must be satisfied. In this work, after optimal unit commitment, following nonlinear AC OPF balanced equality constraints given in Eq. (6) to (7) must be satisfied during NR load flow and these constraints for the entire time horizon are given as;

$$\sum_{t=1}^{T_n} \sum_{i=1}^{Ng} P_i(t)\, u_i(t) = \sum_{t=1}^{Nt} P_D^t * u_i(t) + P_{loss} \tag{6}$$

$$\sum_{t=1}^{Nt} \sum_{i=1}^{Ng} Q_i(t)\, u_i(t) = \sum_{t=1}^{Nt} Q_D^t * u_i(t) + Q_{loss} \tag{7}$$

On the other hand, all the inequality constraints are handled using constraint domination principle (discussed in section), these inequality constraints are;

$$V_{G_i}^{min} \le V_{G_i} \le V_{G_i}^{max} \forall i \in N_G \tag{8}$$

$$P_{G_i}^{min} \le P_{G_i} \le P_{G_i}^{max} \forall i \in N_G \tag{9}$$

$$Q_{G_i}^{min} \le Q_{G_i} \le Q_{G_i}^{max} \forall i \in N_G \tag{10}$$

$$\tau_j^{min} \le \tau_j \le \tau_j^{max} \forall j \in N_\tau \tag{11}$$

$$Q_{c_k}^{min} \le Q_{C_k} \le Q_{C_k}^{max} \forall k \in N_C \tag{12}$$

$$V_{L_p}^{min} \le V_{L_p} \le V_{L_p}^{max} \forall p \in N_L \tag{13}$$

$$S_{l_q} \le S_{l_q}^{max} \forall q \in nl \tag{14}$$

where, V_{G_i} is the voltage set point of ith generator, P_{G_i} and Q_{G_i} are the active and reactive power generation of ith generator, τ_j shows the transformer tap setting of connected in jth branch, Q_{C_k} is the MVAr injection at kth of shunt VAR compensator, V_{L_p} is the pth load bus voltage and S_{l_q} is MVA flow in the qth branch. Whereas min and max superscripts are the minimum and maximum values associated variables.

2) SYSTEM SPINNING RESERVE REQUIREMENTS:

This disparity ensures a technical requirement of power systems, namely the availability of additional generation capacity set aside for risky scenarios, such as the loss of a committed thermal unit, to maintain supply security. It is a linear inequality with continuous variables as well.

$$\sum_{1=1}^{N} P_i^{max} u_i(t) \ge P_D^t + R(t) \tag{15}$$

3) MINIMUM UP AND MINIMUM DOWN CONSTRAINTS

To achieve technical constraints that lower the probability of failure, this inequality is used to ensure that the unit is online for a minimum duration of time since it is started up or that it is offline for a minimum period since it is shut down. It uses integer variables and is linear. Once the unit is committed then it should not be de-committed immediately and if the unit is de-committed it should not be recommitted after a minimum down. In the proposed method min down and min up constraints [45] can be computed as.

$$\sum_{y=t-t_{up}+1}^{t} v^{yi} \le u^{ti} \tag{16}$$

$$\sum_{y=t-t_{down}+1}^{t} \omega^{yi} \le 1 - u^{ti} \tag{17}$$

whereas u, v and ω for ith generator are the binary decision variables for the entire time horizon, value of u is one shows the unit is online whereas zero shows decommitment of i^{th} unit. Value of v is one shows that unit has changes it positions form 0 (at t-1 period) to 1 (at t time slot). On the other hand, ω is the indicator that shows that unit has change it status from 1 to zero. We can make these sums given in Eqs. (16)-(17) "go in a circle" to create a commitment plan that goes from the end of one time period back to the beginning, and we make sure that this plan always works.

4) RAMP-RATE LIMITS FOR UNIT GENERATION CHANGES

A thermal unit's power generation during the prior and current time steps cannot differ by more than the ramping rates thanks to this inequality. It employs continuous variables and is a linear inequality, computed as;

$$P_i(t) - P_i(t-1) \le UR_i - max\left(P_i^{min} - UR, 0\right) \times v_i(t) \tag{18}$$

$$P_i(t-1) - P_i(t) \le max\left(P_t^{min}, DR_i\right) - max\left(P_t^{min} - DR, 0\right) \times u_t^i \tag{19}$$

whereas $P_i(t)$ shows the output power of ith generator at t^{th} time slot. The generation level of ith generator cannot increase or decrease in one hour by more than its ramp up (UR_i)/ ramp down (DR_i) limit, except when it is recommitted. When recommitted (turning on) it must be able to get from zero to its minimum generation level, even if that gap is larger than its ramp up limit. Likewise, when decommitted (turning off), it must be able to get from its minimum generation level down to zero, even if that gap is larger than its ramp down limit. Constraints in Eq. (15)-(19) are dynamic/ intertemporal constraints; therefore, it is necessary to formulate a decision variable that considers dynamic constraints appropriately.

C. DECISION VARIABLES

The study presented in this paper considers load variation in T_n time periods and computes upper and lower bounds of decision variable in the entire time period. In UC problem some constraints such as ramp rate (ramp up and ramp down) and min up and min down constraints are dynamic and these constraints are not satisfied individually. Therefore, in this work, decision variables for each time period are stacked to form a large-scale master problem. In this master problem objective functions and constraints for each time period are treated as separate islands in a stacked network of entire time horizon. Single stacked solution of entire time horizon effectively optimizes the objective function and satisfy all the dynamic intertemporal constraints. The final stacked UC problem allows greater flexibility in the management of power systems, as it provides a single solution for the entire time horizon that can be used to make decisions in real-time. The decision vector for the proposed problem, denoted as $\boldsymbol{x}$, is defined in the study:

$$\boldsymbol{x} = \left[P_i^t, V_i^t, \tau_j, SVC_k, u_i, v_i, w_i\right] \tag{20}$$

where, subscript *i, j* and *k* show the indexes of generators, transformer and shunt VAR compensators, *P* and *V* are the output power of generators and voltage set point of ith generator, τ is transformer tap ratio, u, v $andw$ are the unit commitment, startup and shut down binary variables, 1 if unit is committed, startup or shut down and 0 elsewhere. In the proposed formulation decision variables comprised of mixed integer variables.

III. OPTIMIZATION METHOD

Many real-world applications involve simultaneous optimization of several objective functions, which are often conflicting with each other, and subject to a number of equality and inequality constraints. Unit commitment is a mixed integer nonlinear problem (MINLP) and involve both integer and binary decision variables. Without loss of generality multi-objective optimization problem is stated as;

$$\begin{aligned}
&\min F(\boldsymbol{x}) = (f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x}))\\
&s.t.\ h_i(\boldsymbol{x}) = 0, i = 1, \ldots, p\\
&\quad g_i(\boldsymbol{x}) \leq 0, \quad i = p+1, \ldots, q\\
&\quad \boldsymbol{x} \in \mathbb{R}^n\\
&\quad \boldsymbol{x_i} \in \{\boldsymbol{0}, \boldsymbol{1}\}
\end{aligned} \tag{21}$$

where, $f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x})$ are the m real valued conflicting objective function **s**, *m=1* is for the single objective optimization and value of m is 2 or 3 for the multi-objective optimization. Whereas $h_i(\boldsymbol{x})$ and $g_i(\boldsymbol{x})$ are p and $p - q$ nonlinear equality and inequality and $\boldsymbol{x}$ is the n-dimensional decision vector and $\boldsymbol{x_i}$ is the subset of decision vector that holds sequence of binary constraints.

A. PARETO SET AND PARETO FRONT

In the proposed formulation the i^{th} degree of constraint violation at a given decision vector $\boldsymbol{x}$ can be computed as;

$$c_i(\boldsymbol{x}) = \begin{cases} \max(0, g_i(\boldsymbol{x})), & \forall i \leq p \\ \max(0, |h_i(\boldsymbol{x}) - \epsilon|), & else \end{cases} \tag{22}$$

whereas, ϵ is the tollerance value used to relax the equality constraints. Usually, over all constraint voilation (CV) for all the constraints is computed as;

$$CV(x) = \sum_{i=1}^{q} c_i(\boldsymbol{x}) \tag{23}$$

Decision vector $\boldsymbol{x}$ is feasible if $CV(x)$ is zero, else it is infeasible solution. Pareto set or Pareto optimal solutions (PS) are the set of all solutions that correspond to feasible regions. Image of PS in the objective space is called Pareto Front (PF).

B. PARETO DOMINANCE OR NONDOMINATED SOLUTIONS:

From the randomly selected two decision vectors, say x_u and x_v, x_u is pareto dominance on x_v if $f(x_u) \leq f(x_v)$ for all objective functions and for at least one objective function say j, $f_j(x_u) < f_j(x_v)$, then x_u is said to dominate x_v, and x_u is considered non-dominated solutions.

C. CONSTRAINT DOMINATION PRINCIPLE (CDP):

In this paper constraint domination Principle (CDP) proposed in [46] is applied to handle infeasible solutions. In this technique two solutions are randomly selected and compared as:

- If both solutions $\vec{x}_u$ and $\vec{x}_v$ are infeasible, select $\vec{x}_u$ if $CV(x_u) < CV(x_v)$.
- x_u is feasible and x_v is infeasible, select the feasible one i.e., x_u.
- If both x_u and x_v are feasible, then select x_u if for all the objective functions $f_i(x_u) \leq f_i(x_v)$.

D. PROPOSED HYBRID EVOLUTIONARY ALGORITHM

UC problem is a mixed integer non-linear problem (MINLP), and the optimal solution of MINLP is hard to find using classical optimization techniques. Moreover, the complexity of proposed UC problem is highly increased with the satisfaction of network security constraints. Classical optimization techniques are unable to find the optimal solution of such problem. In the last few decades, evolutionary algorithms (EAs) were efficiently applied to solve the hard MINLP problems. Therefore, in this paper, hybrid real and binary coded Genetic Algorithm (GA) based methodology is applied to solve the proposed UC problem. For Multi-objective UC problem, bidirectional coevolution based MOEA techniques proposed in [47] is hybrid with the proposed variation operators has been applied to find the optimal solution of bi and tri objective functions. For the application of GAs, a simple binary solution was chosen to encode a u, v and w variables. If N represents the number of units and T the scheduling period in hours, then with the assumption that at every hour a certain unit can be either ON or OFF. In such a string, a '1' at a certain location indicates that the unit is ON at this particular hour while a '0' indicates that the unit is OFF. By concatenating the strings of the N units an N-H bit string is formed. In the proposed formulation, UC problem is solved by two separate measures. In the first step, UC decision variables are obtained using binary coding, in this step, all the constraints of UC variables i.e., minimum up and down, spinning reserves and security constraints are checked. However, in the second step, decision variables of UC problems are passed to compute feasible solutions by applying load flow techniques. Before, the evaluation of objective function it is desirable to repair the constraints of the OPF these are ramp up and ramp down. After satisfying all the constraints given in Eq. (5)-(13), total operating cost along with start-up cost, Cost of energy loss and VD objective functions are computed, and obtaining an economical unit commitment schedule, which satisfies the system operating constraints. The Unit Commitment (UC) problem represents a complex multi-objective optimization challenge, involving dynamic and security constraints. Typically, in such scenarios, the Pareto-optimal solutions are located along the edges of these constraints. The primary goal of Multi-Objective Evolutionary Algorithms (MOEAs) is to enhance the diversity and convergence of the Pareto Front (PF). However, accomplishing these objectives is far from straightforward, especially given the intricacies of network security constraints. While most MOEAs aim to optimize the problem to emphasize feasible solutions, they may give rise to the following two issues.

1) Population becoming trapped within local feasible areas or locally optimal feasible regions.

2) The driving force may be constrained as the population's evolution is limited to the feasible portion of the search space.

To address these challenges, the proposed algorithm explores the search space by coevolving two populations: the feasible main population (P_t) and the representative infeasible archived population (A_t) [47]. The proposed algorithm effectively guides solutions towards the PF from both the feasible main population and the infeasible archive population sides of the search space, a crucial aspect in CMOP. Additionally, a novel angle-based density (AD) selection scheme is introduced to update the P_t and A_t. This scheme not only preserves search diversity, aiding the discovery of more feasible regions, but also keeps infeasible solutions close to the PF, thereby accelerating the quest for Pareto-optimal solutions. To harmonize the interactions between the main and archive populations and leverage their complementary information, the proposed algorithm incorporates a new restricted mating selection mechanism. The flow diagram of proposed algorithm is shown in Fig. 1.

As shown in flow chart, first load the data of proposed test network, parameters of UC problem and parameters of proposed algorithm and then evaluate the randomly generated initial population to evaluate and compute the objective functions. After that check the terminating condition if satisfied terminate the algorithm and save the result. If the terminating condition is not satisfied, in the second step hybrid variation operators, such as mutation and crossover, is applied on the population that is in mating selection, binary tournament selection, to find the new population called Offspring (Q_t).

To enhance the convergence and diversity of the PF, it's beneficial to encourage interaction and cooperation between main P_t and archive A_t population. The main population, which operates within the feasible search space, and the archive population, which explores promising infeasible solutions. Parents for the mating pool are selected using Binary tournament selection. If the size of the archive population $\|A_t\|$ is smaller than the total population size (N), parents are chosen from the combined population of the P_t and the A_t. However, if the archive size is equal to or larger than N, parents are alternately selected from the main and archive populations based on their CV as defined in Eq. (9) and their angle-based density (AD). First to form mating pool (tournament selection), in which two solutions are randomly picked form P_t (say x_1) and A_t (say a_1) and select the one with smaller CV. After that another two solutions are randomly selected from P_t (say x_1) and A_t (say a_1) are randomly selected, and compared to select the one with the higher AD. In this proposed algorithm, the AD is calculated by normalize the objective functions using *ideal* Z^i_{min} and *nadir* Z^i_{max} points in the C_t according to;

$$f_i'\left(x_j\right) = \frac{f_i - Z^i_{min}}{Z^i_{max} - Z^i_{min}}, i = 1, 2, \ldots, m \tag{24}$$

The normalized objective functions are shown as $F_i'\left(v_j\right) = \left(f_1'\left(v_j\right), f_2'\left(v_j\right), \ldots, f_m'\left(v_j\right)\right)$. After that vector angle between two solutions say x_j and x_k is computed as

$$\theta'_{x_j,x_k} = \arccos\left|\frac{\boldsymbol{F}'\left(x_j\right)\cdot\boldsymbol{F}'\left(x_k\right)}{\left\|\boldsymbol{F}'\left(x_j\right)\right\|\left\|\boldsymbol{F}'\left(x_k\right)\right\|}\right| \\ where\ x_k \in \mathcal{P}_t \cap x_k \neq x_j \tag{25}$$

Next, the solutions are ranked based on the angle between them, where a larger angle corresponds to a higher rank for the solution, making it a promising candidate for mating selection. The idea is to mate one solution with a favorable CV and another with a favorable AD value. This strategy is expected to produce offspring that are not only in converge to the Pareto Front (PF) but also exhibit good diversity.

Once the mating parents are selected, variation operator is applied to find the new solutions called Offspring. In the variation operators first decompose the population into binary and continuous decision variables. After that uniform crossover and bitwise mutation has been applied to vary binary decision variables to form binary part of Offspring and the well-known Simulated Binary Crossover (SBX) and polynomial mutation techniques are applied to generate the continuous offspring. After that binary and continuous decision variables are combined and evaluate the Offspring population. In the next step, main population and archive populations are updated.

Updated main population (A_{t+1}) is obtained by combining the previous main population (A_t) and recently generated offspring population (Q_t) to form combined population C_t and extract the set of feasible S_1 (where $CV \leq 0$) and infeasible S_2 (where $CV > 0$) solutions from C_t. If the size of $S_1 < N$ then sort the infeasible solutions S_2 and select the first $N - S_1$ solutions from sorted S_2. On the other

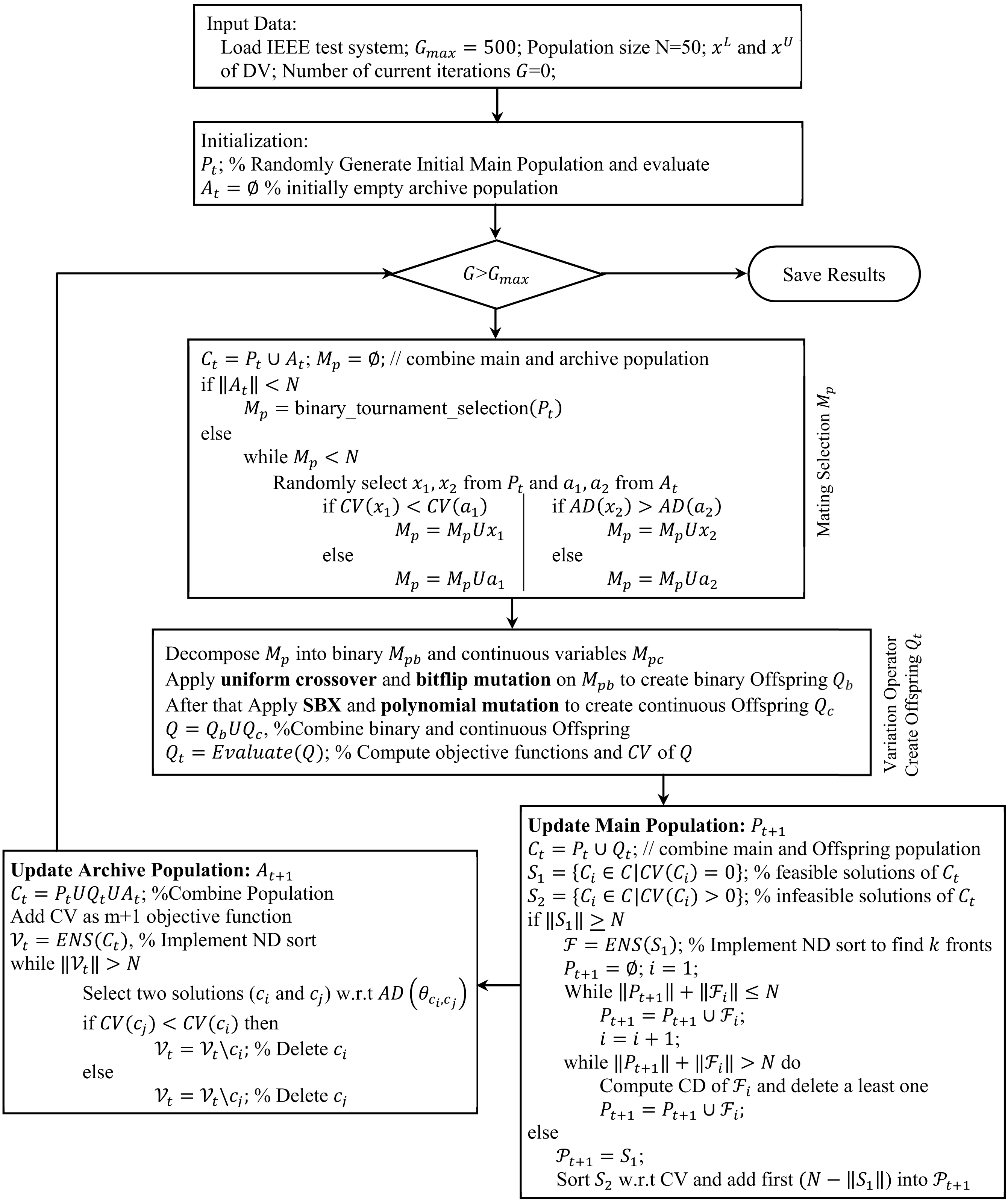

FIGURE 1. Flow chart of proposed hybrid algorithm.

hand if the size of $S_1 > N$ apply fast non-dominated sorting operator discussed in [46] on S_1 to compute the rank of PF say $\mathcal{F}_1, \ldots, \mathcal{F}_k$ ($\mathcal{F}_1$ is the highest rank, $\mathcal{F}_2$ is next highest rank and so on) and assign the highest rank PF to P_{t+1} than 2$^{\text{nd}}$

highest and process is continuous until size of P_{t+1} is equal to N or greater than N. If the size of P_{t+1} is greater than N, than some of the solutions in the last front are eliminated using crowding distance (CD) operator [46].

Finally, update archive population A_{t+1} which is responsible to generate representative non-dominated infeasible solutions by adding CV as one extra objective function and apply unconstrained fast non-dominated sorting $M + 1^{th}$ objective function. Now, copy all the infeasible non-dominated solutions into the archive A_{t+1}. If the number of solutions exactly matches the archive size or is less, proceed to the next stage. If not, utilize a truncation operator to remove surplus infeasible solutions based on their AD and CV. In the truncation process, pick two solutions based on the smallest angle between them, and eliminate the one with the greater constraint violation.

IV. SIMULATION RESULTS

To examine the reliability and efficiency of the proposed method, the IEEE RTS-test system (eleven units) [48] and IEEE 30-bus test network (six units) [49] are adopted to find the solution of optimal UC problem. The number of populations is selected as 40 and the maximum function evaluation is taken as 100000 when there are no network flow constraints and 200000 for the network flow constraints. The program is run on the Corei7 intel with MATLAB version R2023a. Furthermore, to validate the efficiency and superiority of the proposed method three study scenarios are formulated to find the optimal solution of UC problem with and without network security constraints by selecting single and multi-objective functions on a solution of IEEE 30-bus network. In the Scenario 1, traditional UC problem without network constraints of 11 units are duplicated T_n times to find the solution of optimal UC problem considering week ahead planning. In this scenario, decision variables for each hour are stacked to form a master problem, where intertemporal constraints such as ramp up, ramp down, minimum up and down time are easily satisfied to find the near global optimal solutions. In **Scenario 2**, various economical and technical single objective functions such as cost of thermal generators, cost of energy loss and voltage deviation are considered to find the optimal solution of UC problem, there is also state-of-the-art single objective evolutionary algorithms are implemented and compared with the proposed hybrid evolutionary algorithm. In **Scenario 3**, various technical and economical multi-objective objective functions, comprised of cost energy supplied and startup cost, VD and CEL are simultaneously optimized and find the tradeoff between technical and economical objective functions to compute the solution of security constrained UC problem.

A. SCENARIO 1: SIMULATION RESULTS OF SINGLE OBJECTIVE WITHOUT NETWORK SECURITY CONSTRAINTS

Table 1 shows the max, and min power capacity of each generator and their quadratic cost and constraint parameters. Simulation results of selected 24 hours of a day is shown in Table 2, whereas scheduled load demand of a week-ahead (168 hours) of a seven days and power produced by each committed generators with cumulative cost of active power generation are given in Fig. 2.

For better visualization, Table 2 shows the simulation results of only day 6 (starting from 121 to 144 hours), where the peak load has appeared analyzed. Table 2 shows that the proposed method can find a feasible solution, whereas all the solutions are feasible. It can be noticed from Table 2 that all 11 generating units were seen to be committed from time 128hrs to 138hrs (at peak load hours), and a majority of the units were operating at their maximum power capacity in that time frame. Simulation results gives minimum cost subject to satisfying ramp rate, min up and down time constraints. During the sixth day, when the load is maximum, it satisfies the reserve constraint. After examining the results of the sixth day, it can be easily predicted that the G_1 to G_5 are highly efficient generators and committed during base load conditions.

The marginal cost of these generators is less compared to G_6 to G_{11}, hence committed during the entire proposed time horizon. Generators G_6 to G_{11} are frequently decommitted and recommitted according to load profile and their cost curve. Further, Fig. 2 shows the scheduling of generators and cost curve for the entire 168 hours. Fig. 2(a) shows the variation load curve in week, Fig. 2(b) clearly shows that the proposed algorithm gives optimal UC solutions subject to satisfying the UC constraints in all the 168 time slots. The proposed method finds a near globally optimal solution to the UC problem without violating any constraints in week ahead planning. To show the validation and performance of a proposed method, Fig. 2(b) on and off states of generators follow the load curve.

It is depicted in Fig. 2(b), that the maximum share of load supplied by generators is 1 to 6 (that means these generators are economical to supply load demand without operational constraints). Also shows that the optimal UC binary decision variables and majority of units i.e. G_1 to G_6, high-efficiency generators, were operating at their maximum power capacity in that time frame. It can be also noticed from Fig. 2(b) that all 11 generating units were seen to be committed from time 128hrs to 138hrs, and a majority of the units were operating at their maximum power capacity in that time frame. Since the min-up and min-down times of unit 4 are 5hrs each, it stays de-committed during the 48^{th} – 53^{rd} hr and 145^{th} – 149^{th} hr of 6hrs and 5hrs respectively. This is because the load decreases and makes units 2 and unit 3 run on their minimum power ratings. The power rating of unit 4 gradually increases at the instances of 55^{th}, 79^{th}, $102^{nd,}$ and 126^{th} hr where the load increased, and it also forced maximum generators to go online. As compared to units 3, 5, 6, 7, 8, 10, and 11, the 9^{th} Unit is committed first in starting hours as it shares the economic power since it does not approach its maximum power during the whole course. Unit 11 remained de-committed most of the time due to its

TABLE 1. Generator data of RTS system for week ahead optimal UC.

Gen. #	P^{min}	P^{max}	A	B	C	SU	RU	RD	MUT	MDT
1	100	800	5	4	0.0010	415.0			5	5
2	100	800	5	6	0.0020	625.0			5	5
3	80	400	20	8	0.0025	676.0			1	3
4	80	400	20	10	0.0025	836.0			5	5
5	60	300	30	10	0.0020	637.2			4	1
6	60	300	30	12	0.0020	757.2	15	15	1	3
7	50	200	40	14	0.0015	743.7			2	5
8	50	200	40	16	0.0015	843.7			3	4
9	25	100	55	15	0.0012	430.7			5	5
10	25	100	55	17	0.0012	480.7			5	4
11	25	100	55	17	0.0012	480.7			1	1

TABLE 2. UC values and ratings of scenario 1 (from 121 to 144 hours).

Time (hours)	Generators Scheduled Power											$\sum_{i=1}^{11} P_{G_i}$	f_1 ($/h)
	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_8	G_9	G_{10}	G_{11}		
121	796.5	622.5	252.2	116.1	122.9	0	54.8	0	0	0	0	1964.9	14543.3
122	778.4	652.6	240.8	81.3	102.2	0	53.5	0	0	0	0	1908.7	13796.3
123	794.0	626.8	204.6	110.4	116.6	0	0	0	0	0	0	1852.6	12669.1
124	797.8	607.1	185.0	132.0	102.7	0	0	0	0	0	0	1824.5	12229.1
125	781.6	643.0	216.0	112.7	99.2	0	0	0	0	0	0	1852.5	12572.7
126	799.9	722.9	255.9	152.4	129.2	60	0	50	25	25	25	2245.5	20714.1
127	799.9	788.9	284.0	192.4	121.1	63.8	0	54.6	27.4	25.6	0	2357.8	18532.2
128	800	800	324.0	232.4	151.1	93.8	50	74.6	37.4	35.6	25	2646.6	22511.1
129	800.0	799.7	364.0	272.0	180.6	123.8	63.2	94.6	40.1	36.3	32.7	2806.9	24046.9
130	799.2	799.9	398.2	310.5	206.5	153.8	80.1	109.7	48.6	36.0	35.9	2975.4	26274.9
131	799.1	792.2	387.7	341.0	214.4	181.7	73.3	126.1	45.9	40.5	31.2	3033.4	27045.3
132	795.2	789.5	385.6	378.9	218.7	204.0	76.7	131.4	36.6	37.8	36.7	3089.3	27692.0
133	791.9	797.4	379.0	395.5	218.9	210.9	78.8	142.7	39.9	43.7	45.8	3147.9	28535.1
134	797.6	781.7	397.1	399.1	230.6	240.8	95.1	135.1	30.1	40.4	53.7	3201.6	29121.7
135	788.2	791.6	397.1	399.3	227.1	241.4	84.0	117.5	39.1	31.1	57.3	3173.6	28740.9
136	760.5	787.7	366.6	391.0	250.8	214.9	70.9	129.0	29.7	29.6	62.8	3090.5	27778.1
137	742.3	724.6	331.0	356.9	261.6	217.8	67.4	130.8	39.6	37.2	52.9	2973.2	26335.4
138	696.9	681.7	291.0	331.5	250.9	203.1	54.1	110.8	29.6	27.2	42.9	2720.3	23414.5
139	775.9	624.9	306.8	291.5	221.8	173.1	0	90.8	25.3	0	33.0	2542.9	21062.6
140	758.8	659.7	284.4	255.6	198.2	143.1	0	71.2	0	0	0	2370.9	18854.2
141	799.9	590.7	251.3	215.6	176.2	118.9	0	51.2	0	0	0	2203.8	16869.3
142	719.9	510.7	211.3	175.6	146.2	88.9	0	0	0	0	0	1833.2	13039.0
143	717.2	460.2	190.8	135.6	144.9	0	0	0	0	0	0	1648.6	11407.4
144	637.2	380.2	150.8	95.6	114.9	0	0	0	0	0	0	1378.6	9272.4

lowest min-up and min-down time i.e., 1hr. From Fig. 2(c), we can see that the proposed algorithm gives minimum cost subject to satisfying constraints. It also compares the overall cost of Lagrangian Relaxation (LR) and the proposed method, in which LR performs marginally better than the proposed algorithm in some time slots 1. Whereas, in overall time slots proposed method beats the LR method. The proposed method gives a feasible solution compared to the LR method. In most of the time slots, the LR method gives infeasible solutions. Moreover, multiple violations were observed by the LR method due to the complexity of operational constraints. The above discussion exhibits that the proposed hybrid binary and real coded GA-based methodology gives the near-global optimal solution to the UC problem, and it is easy to implement on any size of the real problem with less computational complexity.

B. SCENARIO 2: SIMULATION RESULTS OF SINGLE OBJECTIVE CONSIDERING NETWORK SECURITY CONSTRAINTS

In this subsection, proposed UC formulation is applied on IEEE 30-bus test system to find the solution of single objective security constrained UC (SCUC) problem. In this section decision variables of SCUC problem is obtained by selecting three objective functions such as total operating cost, cost of energy loss and voltage deviation. Table 3 shows the generator data of IEEE 30-bus test system, whereas network data is taken form [45]. Fig. 3 Shows the comparison between the state-of-the-art EAs and the proposed algorithm in terms of convergence plots of various technical and economical objective functions applied to the IEEE 30-bus 6-unit system.

The data reported in Fig. 3 are the minimum operation cost, cost of energy loss and VD values in the convergence curve at

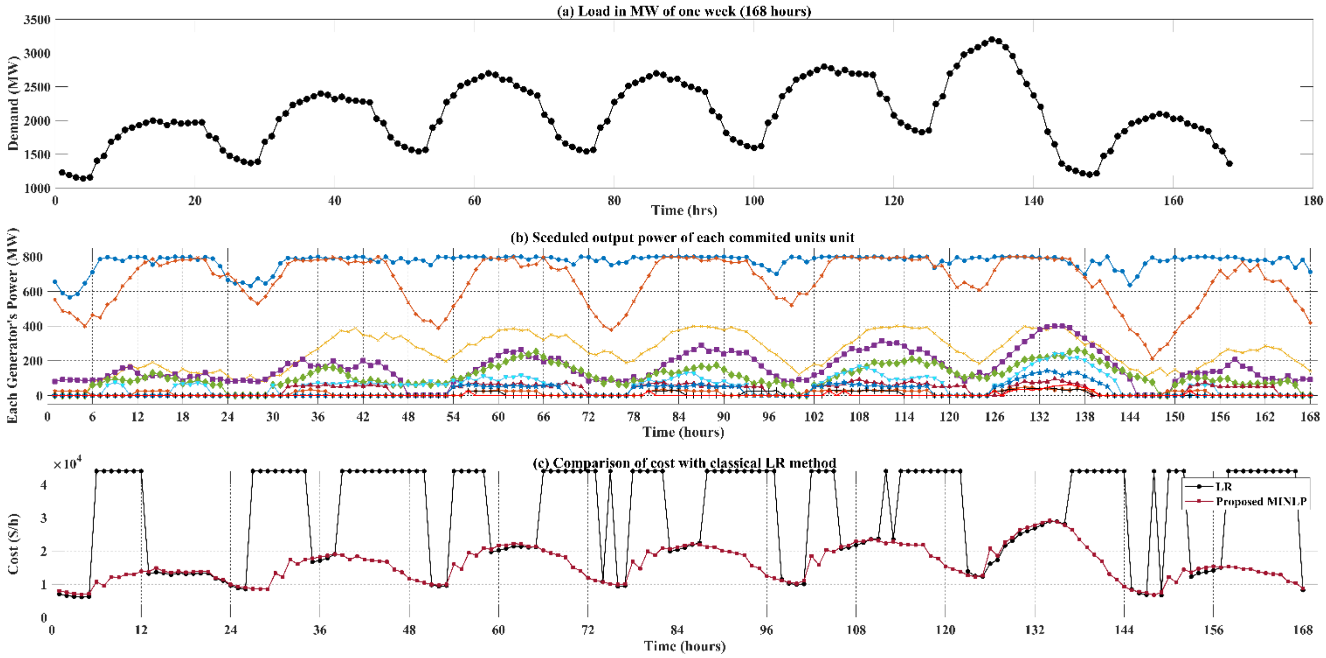

FIGURE 2. Generators and demand of each hour in IEEE RTS system.

each generation during the search. Convergence curve shows that the proposed algorithm and SHADE [50] finds faster convergence compared to all other EAs. After 200 generation in most of the cases proposed algorithm finds near global optimal solution compared to all the other EAs. In all the cases IMODE [51] is stuck in the local optimal solution. From the comparative convergence curve, it is proved that search in both of the direction such as from feasible and infeasible side gives faster rate of convergence to optimal solutions, but with slightly more computational complexity.

In the proposed algorithm high quality infeasible solutions are obtained by converting single objective into bi-objective (second objective function is the overall CV).

After that, nondomination rule has been applied until all the population members are jump into feasible region. Computational cost of proposed algorithm is higher than other algorithms because in the proposed algorithm extra computation is required to find the representative infeasible solutions. These representative infeasible solutions help to increase the convergence of proposed algorithm to find the near global optimal solution. Furthermore, Table 4 shows the comparison of solution of SCUC problem considering various technical and economical objective functions adopting recent evolutionary algorithms. Table 4 describe that the proposed algorithm finds minimum cost of active power generation (objective function in Case 1) and cost of energy loss of thermal generators that are19001.9 $/h and 785.4 $/h respectively compared to all the other algorithms. However, minimum value of startup cost and VD is as shown in SHADE [50] that are 1473.4 $/h and 9.847 p.u, from the simulation results of case 1, it is shown that proposed algorithm find the minimum value of objective function at the cost of increasing other non-optimizing functions. Also, in case 2, proposed algorithm competes all the other algorithm to minimize the Cost of energy loss that is 719.5 $/h after that IMODE [51] find better value of objective function. In case 3 proposed algorithm find better value compared to all the algorithms in all the proposed objective functions. For the better visualization and analysis of decision vector of the proposed algorithm it is desirable to show the decision vector in Figure form.

Fig. 4 shows the sky-blue colored heat map of schedule power of P_g, u, v and w decision variables.In this Fig. 4, dark sky-blue color shows that output power is maximum whereas, light sky-blue shows minimum power produced by those generators and "0" value such as white color shows that generators is shut down. Fig. 4 also depicts that in entire time horizon proposed algorithm finds such solution that satisfy all the intertemporal constraints such ramp up and ramp down constraints and minimum up and down time constraints. Furthermore, Fig. 4 of heat map of schedule power generation clearly shows that during peak hours generators four and five are operated economically. Zero in the Fig. 4 shows that generators are shut down or decommitted during a given time slot. Schedule output power of generators in case 2 and 3 are similar except at some locations of peak hour period. Furthermore, comparison of other decision variables such as transformer tap settings, MVAr injection of static Var compensators (SVC), reactive power generated and startup cost of all the committed units of all the study cases in the entire time hour are shown in Fig. 5. Usually, box chart shown in Fig. 5(a) and (b) gives the statistical information of entire

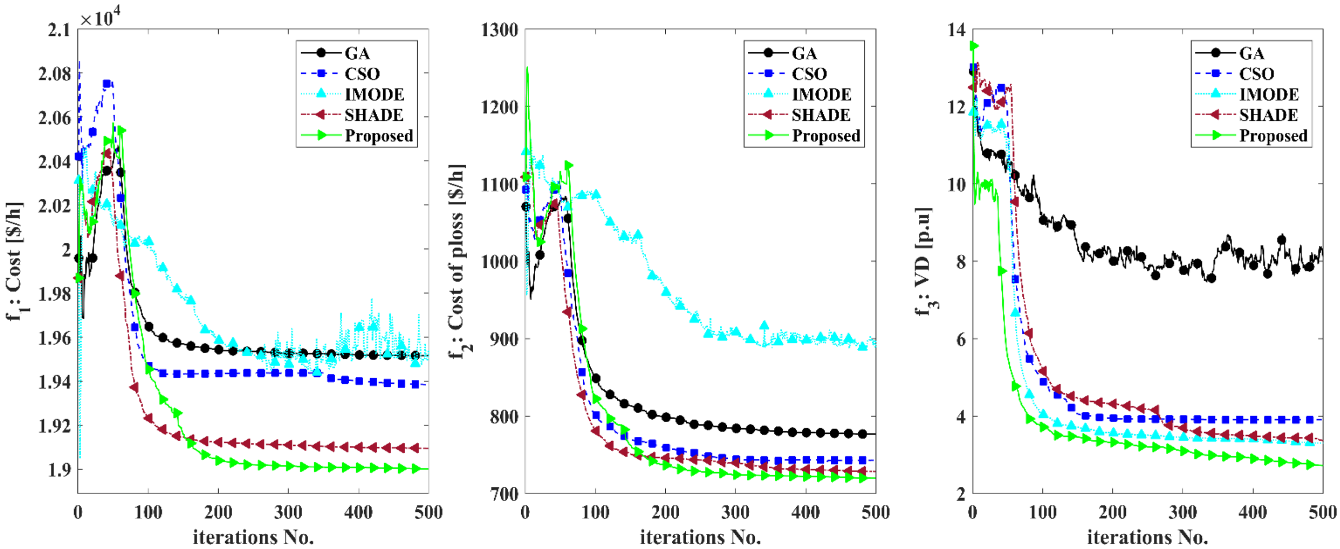

FIGURE 3. Convergence plots of all the cases of competing algorithms.

TABLE 3. Generator data of IEEE 30-bus system for week ahead optimal UC.

Gen. #	P^{min}	P^{max}	A	B	C	SU	RU/RD
1	200	50	0	2	0.0200	250	80
2	80	20	0	1.75	0.0175	142	32
3	80	15	0	1	0.0625	129.062	32
4	50	10	0	3.25	0.0083	133.334	20
5	50	10	0	3	0.0250	132.5	20
6	40	12	0	3	0.0250	139.6	16

TABLE 4. Simulation results of SCUC problem of proposed and the recently implemented EAS.

Case	Algorithm	Cost [$/h]	CEL [$/h]	VD [p.u]	Startup Cost [$/h]
Case 1	GA [52]	19515.9	848.4	15.798	1902.4
	CSO [53]	19384.5	802.3	15.283	1885.8
	IMODE [51]	19095.3	794.7	16.844	1762.8
	SHADE [50]	19538.7	912.8	**9.847**	**1473.4**
	Proposed	**19001.9**	**785.4**	14.967	1762.8
Case 2	GA [52]	19961.8	776.3	15.567	2044.4
	CSO [53]	19768.6	742.9	15.177	1885.8
	IMODE [51]	19501.4	728.2	16.993	1904.8
	SHADE [50]	19642.7	897.2	**10.028**	**1473.4**
	Proposed	**19399.6**	**719.5**	14.785	1904.8
Case 3	GA [52]	21188.1	1196.0	8.110	2171.5
	CSO [53]	18279.5	799.6	3.900	1497.8
	IMODE [51]	18024.7	783.3	3.361	**1495.0**
	SHADE [50]	21505.6	1223.8	3.298	1619.9
	Proposed	**17906.3**	**685.6**	**2.720**	1625.9

time horizon in a single box, this gives minimum, maximum, median and quartile values.

However, plot of each transformer of entire time period is difficult to visualize hence box chart of most of the decision variables are shown to justify the comparative values of decision vectors in various study cases. Fig. 5(a_1) shows the box plot of transformer turns ratio of final optimal solution. Box chart of transformer tap ratio of all the cases is with in specified limit, whereas mean of case 1 and 2 is similar and dissimilar solution produced by case 3. Fig. 5(a_2) shows the box plot of optimal MVAr injection of all the 9 SVCs of final optimal solution. Box chart of SVC injections of all the cases is with in specified limit, whereas mean of case 1 and 2 is similar and higher mean can show in case 3. Fig. 5 (a_3) shows the box plot of optimal MVAr injection of all the committed units of final optimal solution. Box chart of Q_g injection of all the cases is with in specified limit, whereas mean of case 1 and 2 is similar and higher mean

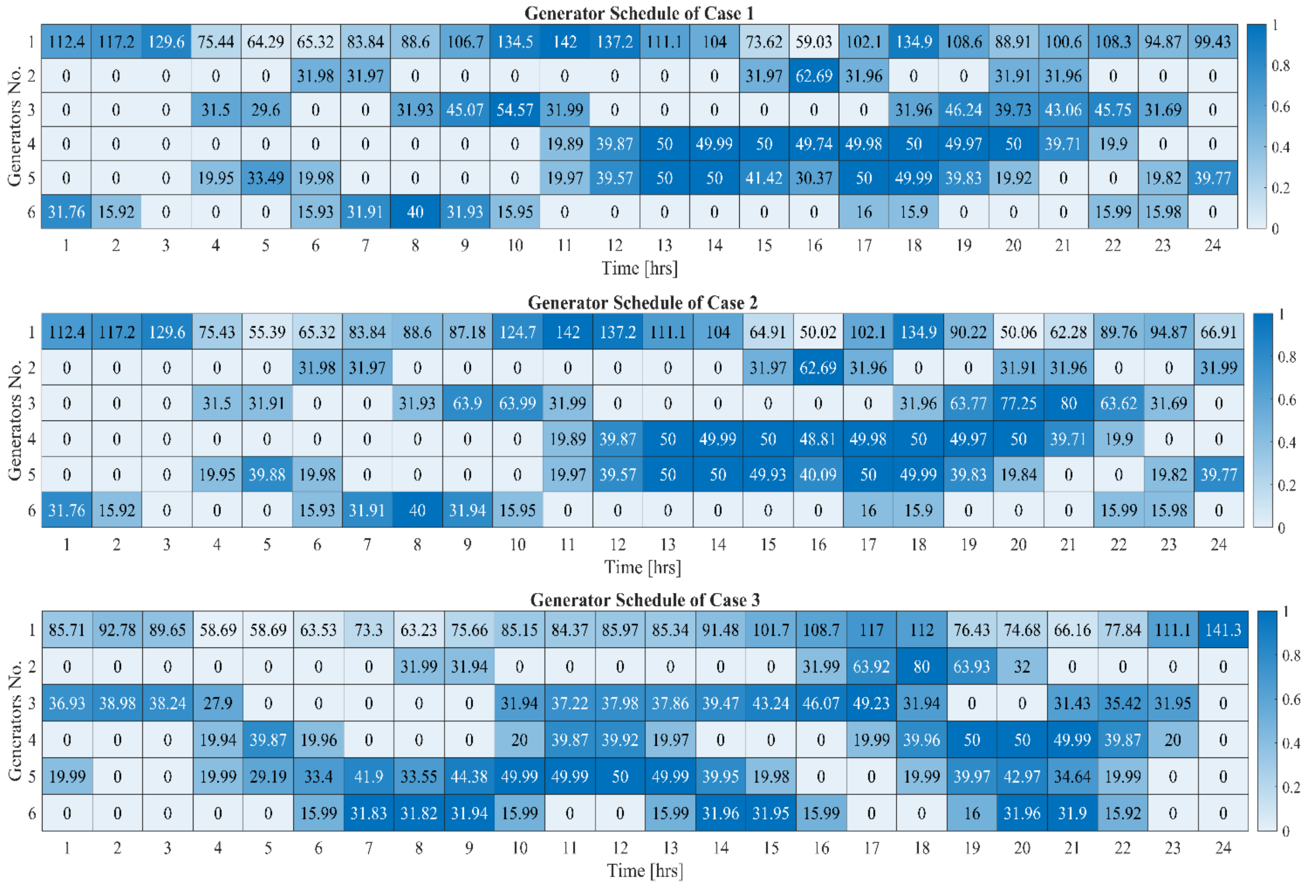

FIGURE 4. Heatmap of schedule power generation P_g and binary SCUC variables.

can show in case 3. Fig. 5(b) shows the voltage profile of all the buses in the entire time horizon of all the study cases. Circles outside the box plot of Fig. 5(b) shows the outlier which are generator bus voltage. Voltage at all the buses is with in specified limit. Over the entire time horizon, the voltage profile of case 3 is ideal (near unity) compared to case 1 and 2. Considering technical objective function such as VD emphasize the decision variable near unity.

Fig. 5(c) shows the startup cost of all the units and cumulative startup cost obtained by proposed algorithm in case 1, 2 and 3 is 1762.8, 1904.8, and 1625.9 respectively. Over all Simulation results of all the study cases shows that economical objective functions such as operation cost (comprised of cost of active power generation and startup cost) and cost of energy loss gives better objective functions whereas, minimum startup cost of generator and value of voltage profile variables are obtained ideal by minimization of VD as objective function. In the literature mostly cost functions are considered to obtain the commitment and schedule of thermal generators, whereas in this paper it is also proved the VD is also find the better results of decision vector compared to economical objective functions. Therefore, in the next subsection multi-objective SCUC problem is solved by considering the trade-off between technical and economical objective functions of various two and objective functions.

C. SCENARIO 3: SIMULATION RESULTS OF MULTIOB5WJECTIVE CONSIDERING NETWORK SECURITY CONSTRAINTS

In this section, recently available MOEAs are implemented to solve multi-objective SCUC problem and the results of all the implemented MOEAs are compared with the proposed hybrid algorithm. Operation cost of active power generation, cost of energy loss and VD are the objective functions to find the solution of SCUC problem along with the consideration of AC network constraints. Fig. 6(a_1 to a_3) shows the comparison of Pareto Fronts (PFs) of all the study cases of final nondominated solutions of all the study cases of entire time horizon. In the PF shown in Fig (a_1 to a_3), most recently MOEAs are implemented to solve proposed multi-objective SCUC problem. These MOEAs includes NSGAII [46], ANSGAIII [54], AGEMOEAII [55], CCMO [56].

Final PF as shown in Fig. 6(a_1 to a_3), clearly shows that proposed algorithm finds the better trade-off between bi and tri objective functions in terms of both convergence and diversity. Fig. 6(a_1 and a_2) clearly shows that in case 1 and 2

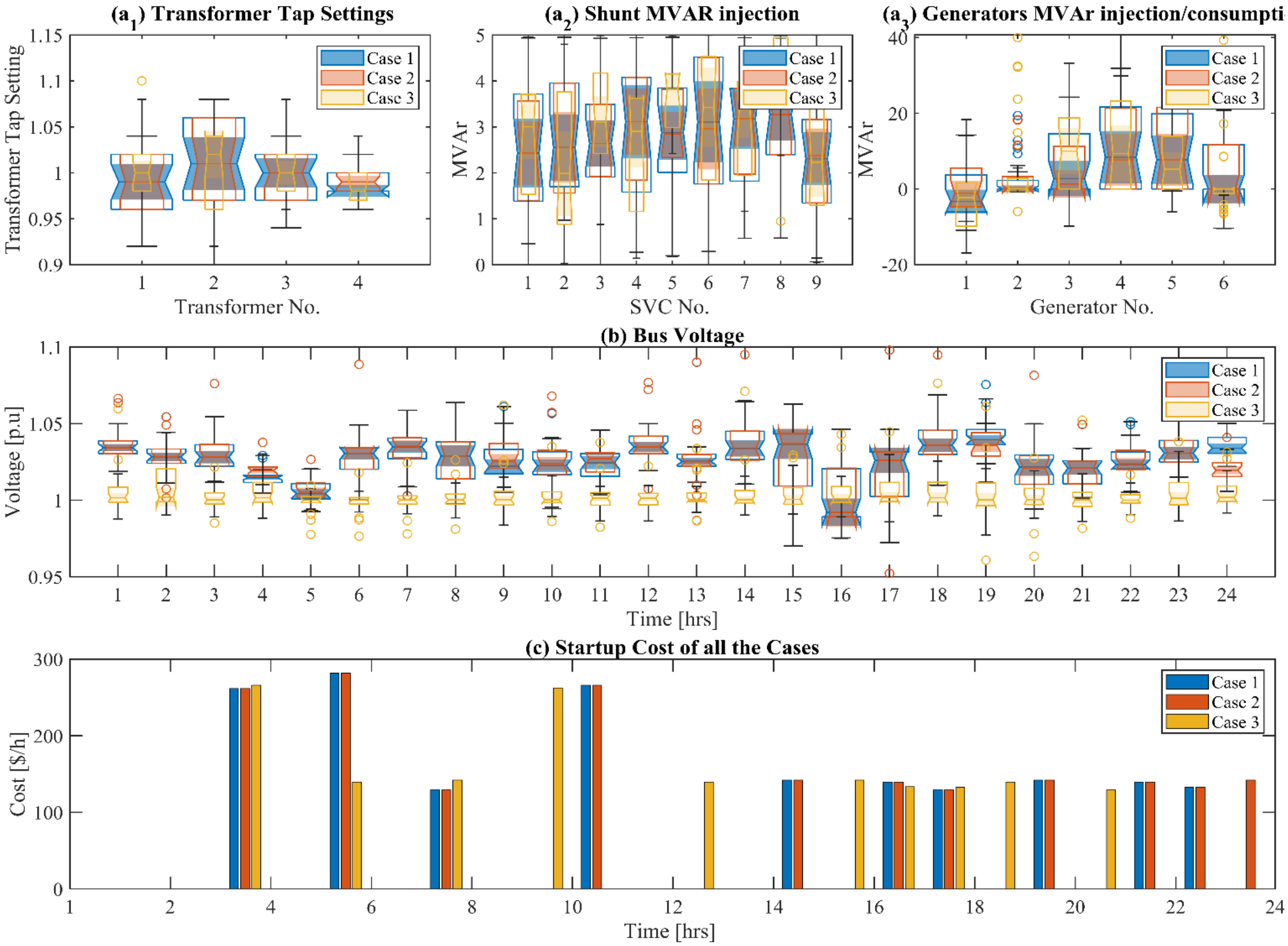

FIGURE 5. Single objective decision variables (a_1) transformer off nominal turns ratio (a_2) Shunt MVAr injection (a_3) reactive power of generator (b) voltage profile of all the buses and (c) startup cost of entire time horizon.

proposed algorithm outperforms the other state of art MOEAs. Whereas, in case 3 it difficult to judge the performance of proposed algorithm with the other state of the MOEAs. In the literature most widely used metric function is HVI that is used to find the performance of MOEAs from the first to the last iteration. In this matric only the worst and best solutions are required from the results of all the algorithm and select the reference point in the objective functions space such as $(1, 1, 1)^m$, whereas m shows the number of objective functions. Maximum value of HVI metric of a MOEA gives the information of better convergence and diversity compared to other MOEAs of complicated PF. In the proposed study cases, HVI helps to compare performance of various MOEAs with the proposed algorithm, especially in case 3 when the performance of MOEAs is not judged to see the PF only. Fig. 6(b_1 to b_3) shows the HVI of all the implemented MOEAs. HVI in Fig. 6 (b_1 to b_3) shows that after each 100 generation in case 1 and 2 and after each 150 generation in case 3 after this iteration proposed algorithm find the feasible solutions. HVI of all the study cases clearly shows that proposed algorithm has better convergence and diversity compared to NSGAII [46], ANSGAIII [54], AGEMOEAII [55], CCMO [56]. The diamond shape in PF shows the best compromise solution (BCS) and, in this study its computed using fuzzy weight functions. The fuzzy decision approach, as described in reference [57], involves first normalize the objective functions space called membership function $\left(\mu_m^k\right)$ as;

$$\mu_m^k = \begin{cases} 1 & for\ f_m^k \leq f_m^{min} \\ \dfrac{f_m^{max} - f_m^k}{f_m^{max} - f_m^{min}} & for\ f_m^{min} < f_m^k < f_m^{max} \\ 0 & for\ f_m^k \geq f_m^{max} \end{cases} \tag{26}$$

The calculation of the membership function μ_m^k involves the use of parameters m and k, which represent the number of objective functions and population size respectively. Once the membership function is computed, it is then normalized to

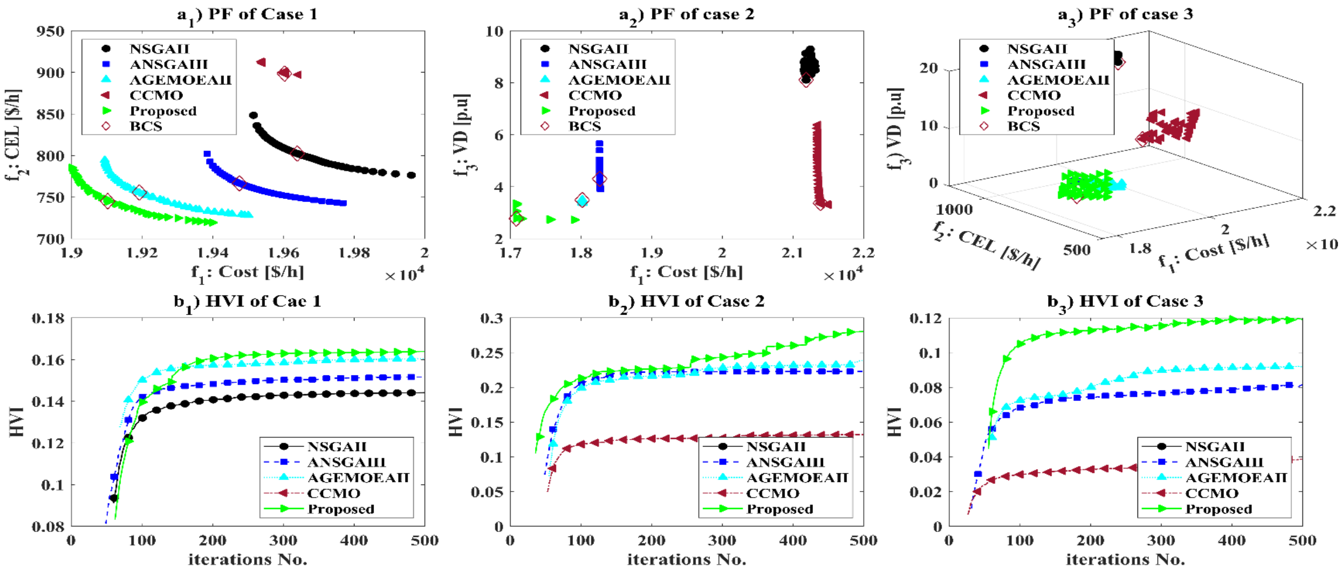

FIGURE 6. Simulation results of multi-objective SCUC Problem (a) Final nondominated PF b) HVI of all the study cases of entire time horizon of all the study cases.

TABLE 5. The simulation results of proposed and the recently implemented EAs available in the literature.

	BCS_PF			min (OF)			max (OF)					Startup
Method	Cost	CEL	VD	Cost	CEL	VD	Cost	CEL	VD	HVI	FR	Cost
NSGAII [46]	19639.7	802.3	15.910	19515.9	776.3	--	19399.6	848.4	--	0.144	100	1902.4
ANSGAIII [54]	19476.1	766.6	15.343	19384.5	742.9	--	19768.6	802.3	--	0.152	100	1885.8
AGEMOEAII [55]	19193.0	755.6	16.990	19095.3	728.2	--	19501.4	794.7	--	0.160	100	1762.8
CCMO [56]	19603.4	898.5	9.966	19538.7	897.2	--	19642.7	785.4	--	0.150	90	**1473.4**
Proposed	**19103.5**	**745.1**	**15.002**	**19001.9**	**719.5**	--	**19961.8**	**912.8**	--	**0.164**	**100**	1762.8
NSGAII [46]	21188.1	1196.0	8.110	21158.7	--	8.1	21315.1	--	9.3	0.110	93	2171.5
ANSGAIII [54]	18267.4	785.6	4.305	18265.2	--	3.9	18279.5	--	5.7	0.223	100	1497.8
AGEMOEAII [55]	18021.6	779.9	3.491	18021.5	--	3.4	18024.7	--	3.5	0.239	100	1495.0
CCMO [56]	21391.8	1202.2	3.371	21352.0	--	3.3	21505.6	--	6.4	0.132	100	1619.9
Proposed	**17088.4**	**589.9**	**2.777**	**17086.1**	**--**	**2.7**	**17906.3**	**--**	**3.4**	**0.280**	**100**	**1353.8**
NSGAII [46]	21179.8	1121.4	16.290	21155.3	1118.7	16.3	21212.3	1151.5	17.7	0.089	78	1631.4
ANSGAIII [54]	18856.8	828.6	3.265	18802.1	814.0	3.2	19019.7	844.7	3.5	0.082	100	1759.8
AGEMOEAII [55]	18975.2	772.8	**2.860**	18892.8	737.4	2.7	19305.9	807.0	3.9	0.092	100	1762.8
CCMO [56]	21149.9	1011.2	4.466	21083.8	851.8	4.4	21547.7	1011.2	10.8	0.039	100	1474.4
Proposed	**17827.8**	**637.9**	5.286	**17679.3**	**584.7**	**4.9**	**18255.4**	**675.5**	**9.4**	**0.120**	**100**	**1212.6**

obtain the normalized membership function μ^{k}.

$$\bar{f}(x) = \sum_{i=1}^{m} \bar{f}_i(x) \tag{27}$$

The value of N_d represents the number of solutions in the final PF (Pareto Front). The BCS can be determined by finding the index with the highest μ^k value. Table 4 displays the BCS results of all algorithms of all the cases that utilized fuzzy decision-making rules. For better visibility, diversity and convergence of PF of proposed algorithm of case 2 and 3 are as shown in Fig. 7. Also, Fig. 7 clearly shows that in the complicated study Cases 2 and 3, proposed algorithm outperforms compared to other recently implemented MOEAs. Fig. 7 also shows that proposed algorithm finds the highly distributed nondominated PF in complex Case 2 and 3. Table 5 gives Simulation results of all the study cases of proposed algorithm and other recently implemented MOEAs.

Table 5 describe that the proposed algorithm finds minimum cost of active power generation (objective functions in Case 1) and cost of energy loss of thermal generators that are 19001.9 \$/h and 719.5 \$/h respectively compared to all the other algorithms. Maximum values of objective functions in Case 1 are 19961.8 and 912.8 \$/h, which are maximum compared to all the other MOEAs. Minimum and maximum values shows that the proposed algorithm find the widely distributed PF. In all the cases feasibility ratio (FR) of most of the algorithms is 100%, except CCMO [56] that some of the population members are stuck in infeasible region. HVI values of proposed algorithm are shown maximum compared to all the other algorithms.

In case 2, proposed algorithm competes all the other algorithm and values of objective functions f_1, f_2 and f_3 are 17088.4 \$/h, 589.9 \$/h and 2.777 p.u respectively.

However, in Case 3, proposed algorithm finds the minimum values of f_1 and f_2 that are17827.8 \$/h and 637.9 \$/h

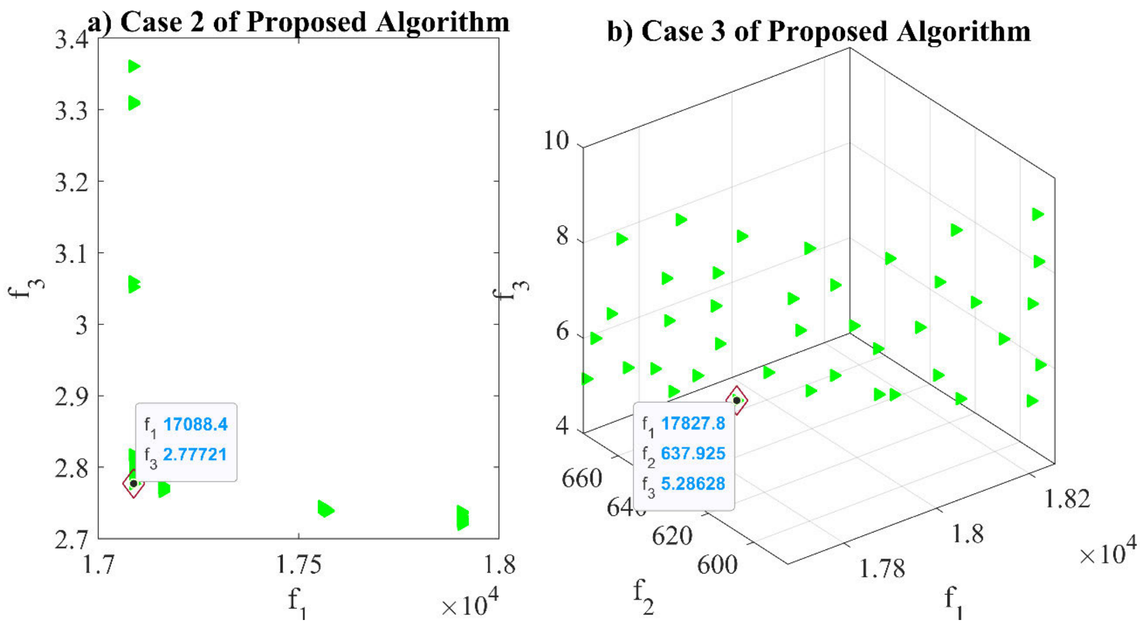

FIGURE 7. Final Nondominated solutions and BCS of Case 2 and 3 of proposed algorithm.

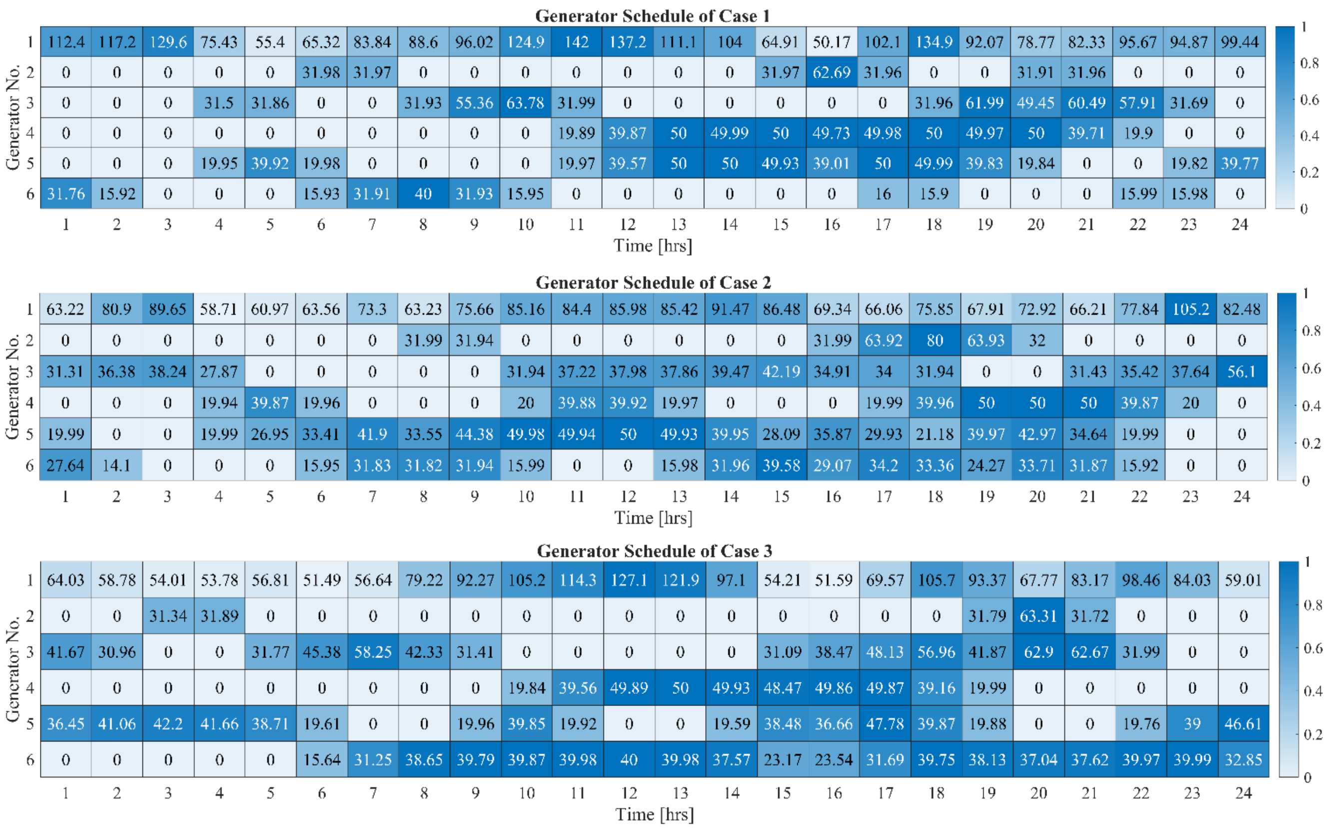

FIGURE 8. Heatmap of schedule power generation P_g and binary SCUC variables (u, v and w) of all the cases.

respectively, whereas, minimum value of f_3 is obtained by AGEMOEAII [55] that is 2.860 p.u. Cumulative startup cost in Case 2 and 3 is recorded by proposed algorithm that are 1353.8 and 1212.6 \$/h, where as in Case 1 minimum cumulative startup cost is figured by CCMO [56] that is 1473.4 \$/h.

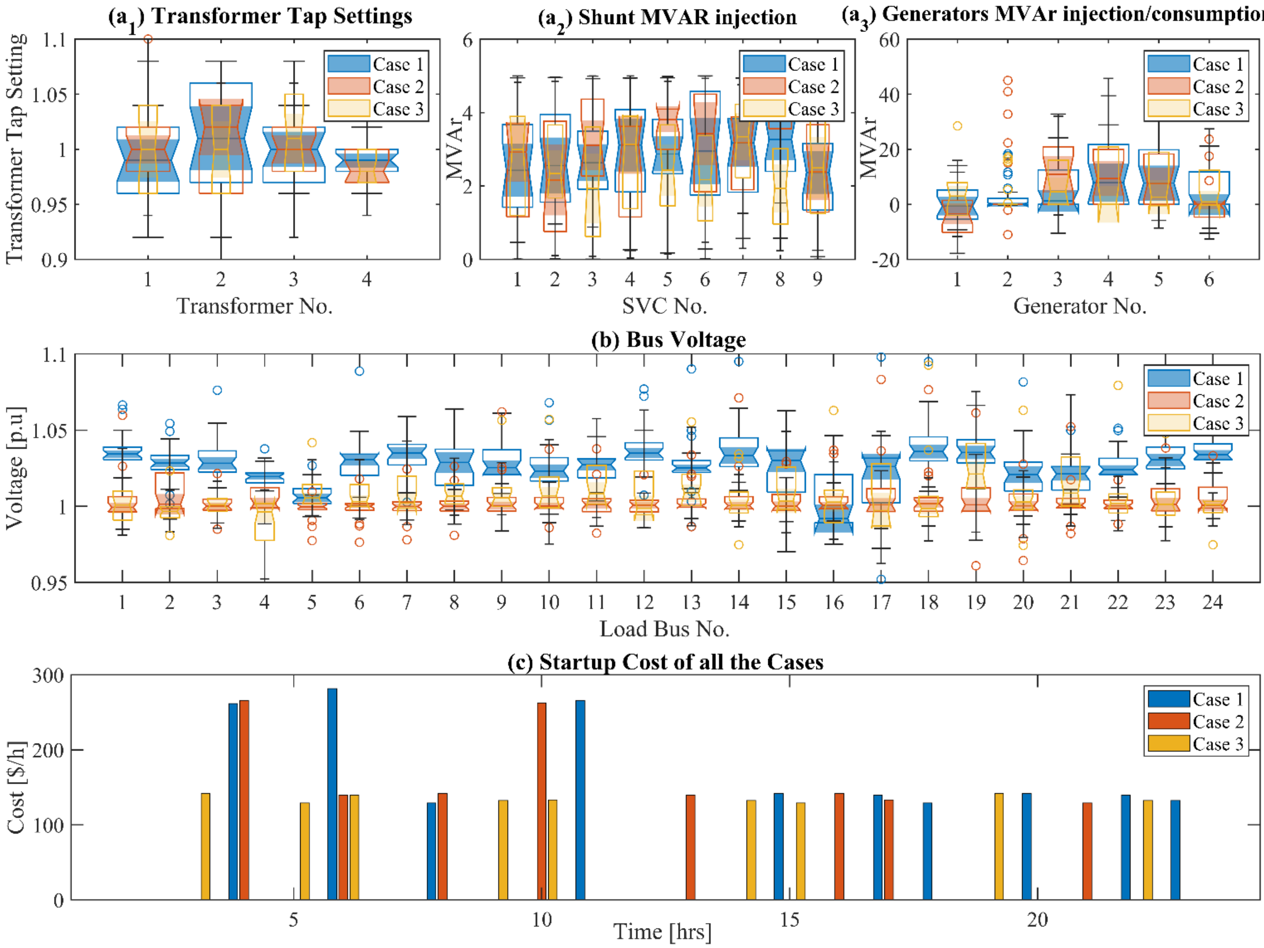

FIGURE 9. Multi-objective objective decision variables of SCUC (a_1) transformer off nominal turns ratio (a_2) Shunt MVAr injection (a_3) reactive power of generator (b) voltage profile of all the buses and (c) startup cost of entire time horizon.

For the better visualization and analysis of scheduling decision vector of proposed algorithm it is desirable to show the decision vector in Figure form. Fig. 8 shows the sky-blue colored heat map of schedule power *Pg,* and binary decision variables *u, v* and *w* of entire time horizon.In the Fig. 8, dark sky-blue color shows that output power is maximum whereas, light sky-blue shows minimum power produced by that generator and "0" value such as white color shows that generators is shut down. Fig. 8 also depicts that in the entire time horizon proposed algorithm finds such solution that satisfy all the intertemporal constraints that includes ramp up and down (ramp rate) constraints and min up and down time constraints. Fig. 8 of heat map of schedule power generation clearly shows that during peak hours generators four and five are operated economically. Zero in the Fig. 8 shows that generators are shutdown or de-committed during a given time slot. Schedule output power of generators in case 2 and 3 are similar except at some locations of peak hour period. Furthermore, comparison of other decision variables such as transformer tap settings, MVAr injection of static Var compensators (SVC), reactive power generated and startup cost of all the committed units of all the study cases in the entire time hour are shown in Fig. 9. In Fig. 9(a) and (b), a box chart is typically employed to display statistical information for the entire time horizon in a single box. This box chart provides key statistical measures, including minimum, maximum, median, and quartile values of decision variables in the entire time horizon.

However, visualizing the line plots of each decision variable over the entire time period can be challenging. Therefore, box charts for most decision variables are presented to facilitate a comparison of decision vectors in various study cases. In Fig. 9(a_1), you can observe the box plot representing the transformer turns ratio of the final optimal solution. The box charts for transformer tap ratios in all cases fall within specified limits. The means of Cases 1 and 2 are similar, while case 3 produces a dissimilar solution with a different mean. Moving to Fig. 9(a_2), we have found the box plot illustrating the optimal MVAr injection for all 9 SVCs in the final optimal solution. The box charts for SVC injections in all cases stay within the specified limits. In Fig. 9(a_3), the box plot shows the optimal MVAr injection of all committed units in the final optimal solution. Similar to the previous cases, the box chart for Q_g injection in all cases complies with the specified limits. The means of cases 1 and 2 are similar, while case 3 features a higher mean. Fig. 9(b) depicts the voltage profiles of all buses throughout the entire time horizon for all study cases. Circles outside the box plots indicate outliers, which correspond to the voltage of generator buses. Voltage levels at all buses remain within the specified limits. Over the entire time horizon, the voltage profile of case 3 is ideal, approaching unity, unlike cases 1 and 2.

This highlights that considering technical objective functions such as Voltage Deviation (VD) places an emphasis on decision variables approaching unity. In Fig. 9(c), the startup costs of all units over the entire time periods are presented. The cumulative startup costs obtained by the proposed algorithm in Cases 1, 2, and 3 are 1762.8 \$/h, 1353.8 \$/h, and 1212.6 p.u, respectively. The simulation results across all study cases reveal that economic objective functions, such as operational cost (comprising cost of active power generation and startup cost) and cost of energy loss, yield superior objective function values. Notably, the minimum startup cost of the generator and the values of voltage profile variables are ideal in case 3, where all three objective functions are minimized concurrently. It's worth mentioning that this paper demonstrates that Voltage Deviation (VD) can yield better results of SCUC problem in decision vectors compared to economic objective functions.

V. CONCLUSION

This paper, embarked on a significant journey to address the intricate challenge of Unit Commitment (UC), specifically focusing on Security Constrained UC (SCUC). The SCUC problem is central to the optimization of power generation unit scheduling within the bounds of numerous operational constraints. In recent decades, there has been a increasing interest in the application of evolutionary algorithms (EAs) to tackle large-scale multi-objective MINLP challenges. This pioneering approach integrates single and multi-objective EAs to navigate the complexities of SCUC, with a unique emphasis on incorporating intricate AC network constraints through hybrid binary and real coded operators. The development of an ensemble algorithm, uniting hybrid real and binary coded operators and extended by a bidirectional coevolutionary algorithm, fortifies the methodology to handle multi-objective SCUC problems effectively. Our study introduces a novel formulation, leveraging three conflicting objective functions to address the SCUC problem. These objectives encompass the minimization of the cost of energy supplied, startup and shutdown costs of generators, the cost of energy loss, and voltage deviation. This versatile formulation has proven its effectiveness in resolving both single and multi-objective SCUC problems, placing emphasis on a harmonious interaction between technical and economical objective functions. Through rigorous testing, our proposed algorithm has exhibited exceptional performance across various scenarios, employing the 11-units IEEE RTS system and the 6-unit IEEE 30-bus test system, both with and without security constraints. We have successfully demonstrated the algorithm's ability to discover solutions that approach global optimality, surpassing other contemporary EAs. The integration of our search operator with a multi-objective coevolutionary algorithm, operating seamlessly with both feasible and infeasible solutions, has shown outstanding performance in addressing multi-objective SCUC problems. Simulation results have been rigorously compared to various recently implemented Multi-Objective Evolutionary Algorithms (MOEAs), clearly demonstrating the superiority of our proposed algorithm in terms of convergence and diversity. Our research also introduces an innovative and highly effective approach for tackling the SCUC problem within the confines of AC network constraints. The outcomes presented in this paper illustrate impressive achievements in terms of optimality and performance, particularly in the context of multi-objective optimization. This work sets the stage for future advancements in the field of power system optimization, with the potential to revolutionize the way we address UC challenges.

ACKNOWLEDGMENT

The authors extend their appreciation to the Deanship of Scientific Research at Northern Border University, Arar, KSA for funding this research work through the project number "NBU-FFR-2024-2448-02."

REFERENCES

[1] N. Yang, Z. Dong, L. Wu, L. Zhang, X. Shen, D. Chen, B. Zhu, and Y. Liu, "A comprehensive review of security-constrained unit commitment," *J. Modern Power Syst. Clean Energy*, vol. 10, no. 3, pp. 562–576, May 2022, doi: 10.35833/MPCE.2021.000255.

[2] Q. P. Zheng, J. Wang, and A. L. Liu, "Stochastic optimization for unit commitment—A review," *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 1913–1924, Jul. 2015, doi: 10.1109/TPWRS.2014.2355204.

[3] N. P. Padhy, "Unit commitment—A bibliographical survey," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 1196–1205, May 2004, doi: 10.1109/TPWRS.2003.821611.

[4] A. Hafeez, A. Ali, M. U. Keerio, N. H. Mugheri, G. Abbas, A. Khan, S. Mirsaeidi, A. Yousef, E. Touti, and M. Bouzguenda, "Optimal site and size of FACTS devices with the integration of uncertain wind generation on a solution of stochastic multi-objective optimal power flow problem," *Frontiers Energy Res.*, vol. 11, Nov. 2023, Art. no. 1293870.

[5] H. Abdi, "Profit-based unit commitment problem: A review of models, methods, challenges, and future directions," *Renew. Sustain. Energy Rev.*, vol. 138, Mar. 2021, Art. no. 110504, doi: 10.1016/j.rser.2020.110504.

[6] L. Montero, A. Bello, and J. Reneses, "A review on the unit commitment problem: Approaches, techniques, and resolution methods," *Energies*, vol. 15, no. 4, p. 1296, Feb. 2022, doi: 10.3390/en15041296.

[7] Z. Wu, Y. Zhuang, S. Zhou, S. Xu, P. Yu, J. Du, X. Luo, and G. Abbas, "Bi-level planning of multi-functional vehicle charging stations considering land use types," *Energies*, vol. 13, no. 5, p. 1283, Mar. 2020, doi: 10.3390/en13051283.

[8] M. Premkumar, R. Sowmya, C. Ramakrishnan, P. Jangir, E. H. Houssein, S. Deb, and N. M. Kumar, "An efficient and reliable scheduling algorithm for unit commitment scheme in microgrid systems using enhanced mixed integer particle swarm optimizer considering uncertainties," *Energy Rep.*, vol. 9, pp. 1029–1053, Dec. 2023, doi: 10.1016/j.egyr.2022.12.024.

[9] V. Kumar, R. Naresh, and V. Sharma, "Profit based unit commitment problem solution using metaheuristic optimisation approach," *Int. J. Syst. Sci., Oper. Logistics*, vol. 10, no. 1, Dec. 2023, Art. no. 2037026, doi: 10.1080/23302674.2022.2037026.

[10] A. Abuelrub and B. Awwad, "An improved binary African vultures optimization approach to solve the UC problem for power systems," *Results Eng.*, vol. 19, Sep. 2023, Art. no. 101354, doi: 10.1016/j.rineng.2023.101354.

[11] J. K. Skolfield and A. R. Escobedo, "Operations research in optimal power flow: A guide to recent and emerging methodologies and applications," *Eur. J. Oper. Res.*, vol. 300, no. 2, pp. 387–404, Jul. 2022, doi: 10.1016/j.ejor.2021.10.003.

[12] A. Ali, G. Abbas, M. U. Keerio, S. Mirsaeidi, S. Alshahr, and A. Alshahir, "Multi-objective optimal siting and sizing of distributed generators and shunt capacitors considering the effect of voltage-dependent nonlinear load models," *IEEE Access*, vol. 11, pp. 21465–21487, 2023, doi: 10.1109/ACCESS.2023.3250760.

[13] A. M. Win and H. Myiauchi, "IGDT-based realistic scheduling of thermal power generators under integration of wind turbine generators," *Int. Rev. Electr. Eng. (IREE)*, vol. 17, no. 2, pp. 105–117, Apr. 2022.

[14] T. Jiang, C. Yuan, R. Zhang, L. Bai, X. Li, H. Chen, and G. Li, "Exploiting flexibility of combined-cycle gas turbines in power system unit commitment with natural gas transmission constraints and reserve scheduling," *Int. J. Electr. Power Energy Syst.*, vol. 125, Feb. 2021, Art. no. 106460, doi: 10.1016/j.ijepes.2020.106460.

[15] A. J. Wood and B. F. Wollenberg, *Power Generation, Operation, and Control*. Hoboken, NJ, USA: Wiley, 2012.

[16] A. Bhadoria, S. Marwaha, and V. K. Kamboj, "An optimum forceful generation scheduling and unit commitment of thermal power system using sine cosine algorithm," *Neural Comput. Appl.*, vol. 32, no. 7, pp. 2785–2814, Apr. 2020, doi: 10.1007/s00521-019-04598-8.

[17] A. Grey and A. Sekar, "Unified solution of security-constrained unit commitment problem using a linear programming methodology," *IET Gener., Transmiss. Distrib.*, vol. 2, no. 6, pp. 856–867, 2008. [Online]. Available: https://digital-library.theiet.org/content/journals/10.1049/iet-gtd_20070367

[18] M. Nozarian, H. Seifi, M. K. Sheikh-El-Eslami, and H. Delkhosh, "Hydro thermal unit commitment involving demand response resources: A MILP formulation," *Electr. Eng.*, vol. 105, no. 1, pp. 175–192, Feb. 2023, doi: 10.1007/s00202-022-01651-z.

[19] Z. Shao, Q. Zhai, Z. Han, and X. Guan, "A linear AC unit commitment formulation: An application of data-driven linear power flow model," *Int. J. Electr. Power Energy Syst.*, vol. 145, Feb. 2023, Art. no. 108673, doi: 10.1016/j.ijepes.2022.108673.

[20] M. E. Nazari and Z. M. Fard, "A novel heuristic optimisation algorithm for solving profit-based unit commitment for thermal power generation with emission limitations," *Int. J. Sustain. Energy*, vol. 41, no. 6, pp. 675–698, Jul. 2022, doi: 10.1080/14786451.2021.1971979.

[21] Y. Yin, C. He, T. Liu, and L. Wu, "Risk-averse stochastic midterm scheduling of thermal-hydro-wind system: A network-constrained clustered unit commitment approach," *IEEE Trans. Sustain. Energy*, vol. 13, no. 3, pp. 1293–1304, Jul. 2022, doi: 10.1109/TSTE.2022.3150918.

[22] S. Zhou, D. He, W. Gu, Z. Wu, G. Abbas, Q. Hong, and C. Booth, "Design and evaluation of operational scheduling approaches for HCNG penetrated integrated energy system," *IEEE Access*, vol. 7, pp. 87792–87807, 2019, doi: 10.1109/ACCESS.2019.2925197.

[23] G. Abbas, M. Hatatah, A. Ali, E. Touti, A. Alshahir, and A. M. Elrashidi, "A novel energy proficient computing framework for green computing using sustainable energy sources," *IEEE Access*, vol. 11, pp. 126542–126554, 2023.

[24] H. O. R. Howlader, O. B. Adewuyi, Y.-Y. Hong, P. Mandal, A. M. Hemeida, and T. Senjyu, "Energy storage system analysis review for optimal unit commitment," *Energies*, vol. 13, no. 1, p. 158, Dec. 2019, doi: 10.3390/en13010158.

[25] C. Wang and S. M. Shahidehpour, "Effects of ramp-rate limits on unit commitment and economic dispatch," *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 1341–1350, Aug. 1993, doi: 10.1109/59.260859.

[26] J. Du, J. Tian, Z. Wu, A. Li, G. Abbas, and Q. Sun, "An interval power flow method based on linearized DistFlow equations for radial distribution systems," in *Proc. 12th IEEE PES Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Sep. 2020, pp. 1–5, doi: 10.1109/APPEEC48164.2020.9220372.

[27] B. Postolov and A. Iliev, "New metaheuristic methodology for solving security constrained hydrothermal unit commitment based on adaptive genetic algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 134, Jan. 2022, Art. no. 107163, doi: 10.1016/j.ijepes.2021.107163.

[28] A. Agarwal and K. Pal, "Optimization of unit commitment problem using genetic algorithm," *Int. J. Syst. Dyn. Appl.*, vol. 10, no. 3, pp. 21–37, Jul. 2021, doi: 10.4018/IJSDA.2021070102.

[29] A. Ali, G. Abbas, M. U. Keerio, M. A. Koondhar, K. Chandni, and S. Mirsaeidi, "Solution of constrained mixed-integer multi-objective optimal power flow problem considering the hybrid multi-objective evolutionary algorithm," *IET Gener., Transmiss. Distrib.*, vol. 17, no. 1, pp. 66–90, Jan. 2023.

[30] J. Raharjo and H. Zein, "Unit commitment effects in economic scheduling of generators," *Int. Rev. Electr. Eng.*, vol. 16, no. 3, pp. 247–256, Jun. 2021.

[31] L. Yang, J. Jian, Y. Wang, and Z. Dong, "Projected mixed integer programming formulations for unit commitment problem," *Int. J. Electr. Power Energy Syst.*, vol. 68, pp. 195–202, Jun. 2015, doi: 10.1016/j.ijepes.2014.12.054.

[32] A. Viana and J. P. Pedroso, "A new MILP-based approach for unit commitment in power production planning," *Int. J. Electr. Power Energy Syst.*, vol. 44, no. 1, pp. 997–1005, Jan. 2013, doi: 10.1016/j.ijepes.2012.08.046.

[33] B. Yang, X. Cao, Z. Cai, T. Yang, D. Chen, X. Gao, and J. Zhang, "Unit commitment comprehensive optimal model considering the cost of wind power curtailment and deep peak regulation of thermal unit," *IEEE Access*, vol. 8, pp. 71318–71325, 2020, doi: 10.1109/ACCESS.2020.2983183.

[34] E. S. Ali, S. M. A. Elazim, and A. S. Balobaid, "Implementation of coyote optimization algorithm for solving unit commitment problem in power systems," *Energy*, vol. 263, Jan. 2023, Art. no. 125697, doi: 10.1016/j.energy.2022.125697.

[35] M. Said, E. H. Houssein, S. Deb, A. A. Alhussan, and R. M. Ghoniem, "A novel gradient based optimizer for solving unit commitment problem," *IEEE Access*, vol. 10, pp. 18081–18092, 2022, doi: 10.1109/ACCESS.2022.3150857.

[36] J.-S. Pan, P. Hu, and S.-C. Chu, "Binary fish migration optimization for solving unit commitment," *Energy*, vol. 226, Jul. 2021, Art. no. 120329, doi: 10.1016/j.energy.2021.120329.

[37] A. Ali, G. Abbas, M. U. Keerio, E. Touti, Z. Ahmed, O. Alsalman, and Y.-S. Kim, "A bi-level techno-economic optimal reactive power dispatch considering wind and solar power integration," *IEEE Access*, vol. 11, pp. 62799–62819, 2023, doi: 10.1109/ACCESS.2023.3286930.

[38] A. R. Jordehi, "An improved particle swarm optimisation for unit commitment in microgrids with battery energy storage systems considering battery degradation and uncertainties," *Int. J. Energy Res.*, vol. 45, no. 1, pp. 727–744, Jan. 2021, doi: 10.1002/er.5867.

[39] A. Shukla and S. N. Singh, "Multi-objective unit commitment with renewable energy using hybrid approach," *IET Renew. Power Gener.*, vol. 10, no. 3, pp. 327–338, Mar. 2016, doi: 10.1049/iet-rpg.2015.0034.

[40] Y.-F. Li, N. Pedroni, and E. Zio, "A memetic evolutionary multi-objective optimization method for environmental power unit commitment," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2660–2669, Aug. 2013, doi: 10.1109/TPWRS.2013.2241795.

[41] F. Bhurt, A. Ali, M. U. Keerio, G. Abbas, Z. Ahmed, N. H. Mugheri, and Y.-S. Kim, "Stochastic multi-objective optimal reactive power dispatch with the integration of wind and solar generation," *Energies*, vol. 16, no. 13, p. 4896, Jun. 2023, doi: 10.3390/en16134896.

[42] R. Mena, M. Godoy, C. Catalán, P. Viveros, and E. Zio, "Multi-objective two-stage stochastic unit commitment model for wind-integrated power systems: A compromise programming approach," *Int. J. Electr. Power Energy Syst.*, vol. 152, Oct. 2023, Art. no. 109214, doi: 10.1016/j.ijepes.2023.109214.

[43] A. G. Trojani, J. M. Baigi, and M. S. Moghaddam, "Stochastic security-constrained unit commitment considering electric vehicles, energy storage systems and flexible loads with renewable energy resources," *J. Modern Power Syst. Clean Energy*, vol. 11, no. 5, pp. 1405–1414, Sep. 2023, doi: 10.35833/MPCE.2022.000781.

[44] G. M. C. Leite, S. Jiménez-Fernández, S. Salcedo-Sanz, C. G. Marcelino, and C. E. Pedreira, "Solving an energy resource management problem with a novel multi-objective evolutionary reinforcement learning method," *Knowl.-Based Syst.*, vol. 280, Nov. 2023, Art. no. 111027, doi: 10.1016/j.knosys.2023.111027.

[45] A. J. Lamadrid, D. Muñoz-Alvarez, C. E. Murillo-Sánchez, R. D. Zimmerman, H. Shin, and R. J. Thomas, "Using the matpower optimal scheduling tool to test power system operation methodologies under uncertainty," *IEEE Trans. Sustain. Energy*, vol. 10, no. 3, pp. 1280–1289, Jul. 2019, doi: 10.1109/TSTE.2018.2865454.

[46] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002, doi: 10.1109/4235.996017.

[47] Z.-Z. Liu, B.-C. Wang, and K. Tang, "Handling constrained multi-objective optimization problems via bidirectional coevolution," *IEEE Trans. Cybern.*, vol. 52, no. 10, pp. 10163–10176, Oct. 2022, doi: 10.1109/TCYB.2021.3056176.

[48] C. Grigg et al., "The IEEE reliability test system-1996. A report prepared by the reliability test system task force of the application of probability methods subcommittee," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 1010–1020, Aug. 1999, doi: 10.1109/59.780914.

[49] A. Ali, G. Abbas, M. U. Keerio, S. Mirsaeidi, S. Alshahr, and A. Alshahir, "Pareto front-based multiobjective optimization of distributed generation considering the effect of voltage-dependent nonlinear load models," *IEEE Access*, vol. 11, pp. 12195–12217, 2023, doi: 10.1109/ACCESS.2023.3242546.

[50] R. Tanabe and A. Fukunaga, "Success-history based parameter adaptation for differential evolution," in *Proc. IEEE Congr. Evol. Comput.*, Jun. 2013, pp. 71–78, doi: 10.1109/CEC.2013.6557555.

[51] K. M. Sallam, S. M. Elsayed, R. K. Chakrabortty, and M. J. Ryan, "Improved multi-operator differential evolution algorithm for solving unconstrained problems," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2020, pp. 1–8, doi: 10.1109/CEC48606.2020.9185577.

[52] S. Habib, G. Abbas, T. A. Jumani, A. A. Bhutto, S. Mirsaeidi, and E. M. Ahmed, "Improved whale optimization algorithm for transient response, robustness, and stability enhancement of an automatic voltage regulator system," *Energies*, vol. 15, no. 14, p. 5037, Jul. 2022, doi: 10.3390/en15145037.

[53] R. Cheng and Y. Jin, "A competitive swarm optimizer for large scale optimization," *IEEE Trans. Cybern.*, vol. 45, no. 2, pp. 191–204, Feb. 2015, doi: 10.1109/TCYB.2014.2322602.

[54] H. Jain and K. Deb, "An evolutionary many-objective optimization algorithm using reference-point based nondominated sorting approach—Part II: Handling constraints and extending to an adaptive approach," *IEEE Trans. Evol. Comput.*, vol. 18, no. 4, pp. 602–622, Aug. 2014, doi: 10.1109/TEVC.2013.2281534.

[55] A. Panichella, "An improved Pareto front modeling algorithm for large-scale many-objective optimization," presented at the Genetic Evol. Comput. Conf., Jul. 2022, doi: 10.1145/3512290.3528732.

[56] Y. Tian, T. Zhang, J. Xiao, X. Zhang, and Y. Jin, "A coevolutionary framework for constrained multiobjective optimization problems," *IEEE Trans. Evol. Comput.*, vol. 25, no. 1, pp. 102–116, Feb. 2021.

[57] E. Davoodi, E. Babaei, and B. Mohammadi-Ivatloo, "An efficient covexified SDP model for multi-objective optimal power flow," *Int. J. Electr. Power Energy Syst.*, vol. 102, pp. 254–264, Nov. 2018, doi: 10.1016/j.ijepes.2018.04.034.

AAMIR ALI received the B.E., M.E., and Ph.D. degrees in electrical engineering from QUEST, Nawabshah, Pakistan. He is currently an Assistant Professor with the Department of Electrical Engineering, Quaid-e-Awam University of Engineering Science and Technology (QUEST), Nawabshah, Sindh, Pakistan. His research interests include power system optimization, grid-connected and islanded operation of distributed generation, smart grids, and multi-objective evolutionary algorithms.

ARSLAN SHAH is currently pursuing the master's degree. His research interests include power system optimization, grid-connected and islanded operation of distributed generation, and smart grids.

MUHAMMAD USMAN KEERIO was born in Nawabshah, Pakistan, in December 1965. He received the bachelor's degree in electrical (power) engineering from the Mehran University of Engineering and Technology, Jamshoro, in 1991, the master's degree in control engineering from NUST, Karachi, in 2002, and the Ph.D. degree in controls and robotics from the Beijing Institute of Technology, China, in 2008. His research interests include electrical and control engineering, curriculum development, institutional accreditation, neural networks, and optimization.

NOOR HUSSAIN MUGHERI received the B.E., M.E., and Ph.D. degrees in electrical engineering from the Quaid-e-Awam University of Engineering Science and Technology (QUEST), Nawabshah, Sindh, Pakistan. He is currently an Assistant Professor with the Department of Electrical Engineering, QUEST. His research interest includes power system optimization.

GHULAM ABBAS received the B.Eng. degree in electrical engineering from QUEST, Nawabshah, Pakistan, in 2017, and the M.Eng. degree in electrical engineering from Southeast University, Nanjing, China, in 2019, where he is currently pursuing the Ph.D. degree in electrical engineering. His research interests include distributed generations' integration, planning, and optimization.

EZZEDDINE TOUTI received the B.S. degree in electrical engineering from the Higher National College of Engineers of Tunis, Tunisia, in 1997, the master's degree in electrical engineering from the National College of Engineers of Tunis, Tunisia, in 2005, and the joint Ph.D. degree in induction generators wind turbine, power quality and electric drives from the National College of Engineers of Monastir, Tunisia, and Artois University, France, in 2013. In 2005, he joined the Laboratory of Industrial Systems Engineering and Renewable Energies (LISIER), University of Tunis, Tunisia, as a Research Faculty Member. He is currently an Associate Professor with the College of Engineering, Northern Border University. His research interests include renewable energy, smart grids, electric vehicles, power electronics, and the control of electrical systems.

MOHAMMED HATATAH received the B.Sc. and M.B.A. degrees in electrical engineering from King Abdulaziz University, Saudi Arabia, in 2007 and 2010, respectively, the M.Sc. degree in power systems from Pennsylvania State University, USA, in 2015, and the Ph.D. degree in power electronics from the University of Pittsburgh, USA, in 2021. In 2005, he did a six-month internship at Saudi Aramco, Saudi Arabia, where he worked on distribution equipment design. From 2006 to 2011, he was an Electrical Planning Engineer with Saudi Electricity Company, Saudi Arabia, where he worked on regional planning (110kV). His research interests include power systems, renewable energy, and the control and optimization of power converters. He is a member of IEEE PELS and PES.

AMR YOUSEF received the B.Sc. and M.Sc. degrees from the Engineering Mathematics Department and the Electrical Engineering Department, Alexandria University, in 2001 and 2006, respectively, and the Ph.D. degree in electrical and computer engineering from Old Dominion University (ODU), in May 2012. He was a Postdoctoral Research Associate with the Old Dominion Vision Laboratory, USA. He is currently an Assistant Professor with the Electrical Engineering Department, University of Business and Technology, Saudi Arabia, and the Engineering Mathematics Department, Alexandria University, Egypt. His research interests include optimization approaches, image processing/computer vision, and machine learning algorithms. He is an SPIE Member and OSA Member.

MOUNIR BOUZGUENDA received the B.S. degree in electrical engineering from The Pennsylvania State University, USA, in 1985, and the M.S. and Ph.D. degrees in electrical engineering from Virginia Polytechnic Institute and State University, USA, in 1988 and 1992, respectively. He taught in VA, USA, MD, USA, Washington DC, and Tunisia. He was a Consultant with the Standard Technologies Institute, ML, USA; the Temple Group, Washington DC; and Computer Engineering Services, Sfax, Tunisia. He joined Sohar University, Oman, in 2000, as a Senior Lecturer, and Sultan Qaboos University, Oman, as an Associate Professor, in 2009. Currently, he is teaching electrical and computer engineering. His research interests include renewable energy systems, power systems, and power electronics. He has authored and coauthored many technical articles in these areas.