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RESEARCH ARTICLE

Co-Optimization of Generation and AC Transmission Networks, Considering Reactive Power Allocation and Network Power Losses

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ABSTRACT Generation and transmission network expansion planning (GTNEP) co-optimization models have been developed to enable simultaneous decisions considering investment and operational components. Most works solve the GTNEP using linearized models without considering voltage variables, reactive power constraints, and network power losses, thus resulting in a loss of model fidelity and leading to either sub-optimal or non-feasible expansion plans. Therefore, this work addresses the GTNEP problem by integrating the planning of new generation power plants, transmission lines, reactive power allocation, and the evaluation of network power losses, using the AC model to assess the operational problem. Therefore, the integrated AC-GTNEP problem is tackled using meta-heuristic optimization techniques. The approach was implemented using the Julia programming language and evaluated using the 6-bus Garver, the IEEE 24-bus, and the IEEE 118-bus test systems. The results illustrate that the proposed integrated GTNEP approach yields more cost-effective expansion plans compared to the sequential approach, with total savings of approximately 11.30%, 8.8%, and 2.5% when applied to each test system, respectively.

INDEX TERMS AC model, co-optimization, generation expansion planning, integrated planning, transmission network expansion planning.

NOMENCLATURE

FUNCTIONS

ω	Objective function of the sub-problem.
υ	Objective function of the master problem.
φ^{GIC}	Generation investment cost.
φ_m^{idc}	Interest during construction of candidate power plant.
C_{op}	Total operation cost.
C_{exp}	Total investment cost of transmission lines, and reactive power sources.
C_{loss}	Cost of network power losses.
$LOLP$	Loss of load probability.
φ_i^{LCE}	Levelized cost of electricity of power plant allocated at bus i.
ζ_m	Capital recovery factor of candidate power plant m.

PARAMETERS

c_{ij}^L	Cost of adding a new transmission line between nodes i, j.
φ_m^{inv}	Investment cost of candidate power plant m.
φ_m^{FOM}	Fixed operating and maintenance cost of candidate power plant m.

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φ_m^{VOM}	Variable operating and maintenance cost of candidate power plant m.
φ_m^{fuel}	Fuel cost of candidate power plant m.
P^d	Total active power demand.
Q^d	Total reactive power demand.
P_{pm}	Emission rate of pollution type p by candidate unit m.
P'_{pi}	Existing emission of pollution type p at bus i.
F_{fm}	Consumption rate of fuel type f by candidate unit m.
F'_{fi}	Existing consumption rate of fuel type f at bus i.
n_{ij}^0	Number of existing lines between nodes $i-j$.
$\overline{n}_{ij}$	Maximum number of lines that can be added between nodes $i-j$.
φ_i^q	Cost of reactive power compensation.
φ_i^p	Cost of active load shedding.
φ_i^{loss}	Cost of network power losses.
h	Number of hours in a year.
f_{loss}	Loss factor.
S_b	Base power.
α	Annual discount rate.
χ_m	Lifetime of candidate power plant m.
ψ_m	Capacity factor of candidate power plant m.
η_m	Electrical efficiency of candidate power plant m.
$\varphi_m^{CO_2}$	CO_2 emission cost for candidate power plant m.
φ_m^{oc}	Overnight cost of candidate power plant m.
$\underline{r}, \overline{r}$	Minimum and maximum percentage reserve margin.
$\overline{Y}_p$	Maximum emission of pollution type p.
$\overline{F}_f$	Maximum available quantity of fuel type f.
$\overline{P}_i^g$	Maximum active power generation of the existing power plant at bus i.
$\underline{P}_i^g$	Minimum active power generation of the existing power plant at bus i.
$\overline{Q}_i^g$	Maximum reactive power generation of the existing power plant at bus i.
$\underline{Q}_i^g$	Minimum reactive power generation of the existing power plant at bus i.
$\overline{P}_i^m$	Maximum active power generation by candidate power plant m at bus i.
$\underline{P}_i^m$	Minimum active power generation by candidate power plant m at bus i.
$\overline{Q}_i^m$	Maximum active power generation by candidate power plant m at bus i.
$\underline{Q}_i^m$	Minimum active power generation by candidate power plant m at bus i.
$\overline{P}_{(i)}^c$	Maximum active power generation by fictitious generator at bus i.
$\underline{P}_{(i)}^c$	Minimum active power generation by factitious generator at bus i.
$\overline{Q}_{(i)}^c$	Maximum reactive power generation by fictitious generator at bus i.
$\underline{Q}_{(i)}^c$	Minimum reactive power generation by factitious generator at bus i.
b_i^{sh}	Shunt susceptance at node node i.
g_i^{sh}	Shunt conductance at node i.

SETS

Ω	Set of buses.
Λ	Set of candidate power plants.
Δ	Set of generation outages.
Γ	Set of all rights-of-ways.
Υ	Set of fuel types.
Ψ	Set of pollution types.
$\mathbb{Z}$	Set of integer numbers.

VARIABLES

E_{mi}	Energy produced by power plant type m allocated at bus i.
n_{ij}	Number of added lines between buses i, j.
P_{ij}^{from}	Active power flow through line between buses i, j.
P_{ij}^{to}	Active power flow through line between buses j, i.
Q_{ij}^{from}	Reactive power flow through line between buses i, j.
Q_{ij}^{to}	Reactive power flow through line between buses j, i.
Q_i^c	Reactive power compensation allocated at bus i.
P_i^c	Active load shedding at bus i.
P_i^m	Active power delivered by power plant type m allocated at bus i.
Q_i^m	Reactive power delivered by power plant type m allocated at bus i.
P_i^g	Total active power generation at bus i.
Q_i^g	Total reactive power generation at bus i.
V_i	Voltage magnitude at bus i.
θ_i	Phase angle of the voltage at bus i.
u_{mi}	Indicates whether power plant type m is constructed at bus i.
p_κ, P_κ	Probability and cumulative probability of generation outage κ.
t_κ	Period of lost load during generation outage κ.

I. INTRODUCTION

The electrical power supply system aims to provide energy to users while meeting quality, reliability, and safety criteria at a minimum cost. Planning for the operation and expansion of the electrical system across the entire supply chain is essential to achieve these objectives. In this context, Generation Expansion Planning (GEP) often relies on a single node model [1], [2], where it is assumed that all generation units and loads are concentrated on a single bus. Conversely, when addressing Transmission Network Expansion Planning (TNEP) [3], [4], it is assumed that the location and capacity of the new generation units are known. Typically, generation and transmission network expansion planning have been addressed sequentially [5], with GEP being solved first, and the resulting expansion plan is then used as an initial condition to address the TNEP problem. This approach was usually accepted considering that more than 80% - 90% of investments are related to GEP and that siting constraints typically determined the location of power plants, with transmission costs being of lesser concern. However, solving the GEP and TNEP problems successively leads to sub-optimal solutions or costly proposals due to oversized transmission expansion plans or high energy production costs.

According to [6], co-optimization of generation and transmission network expansion planning is gaining more attention due to several key factors. The increasing costs and political challenges associated with siting and permitting extra high voltage (EHV) transmission lines have made coordinated planning more attractive. The flexibility and lower capital intensity of natural gas-fired facilities, as well as advancements in dry cooling technologies, have also contributed to this trend. Additionally, integrating remote renewable resources, often far from major load centers, requires comprehensive planning to balance high-quality resources with substantial transmission investments. Industry restructuring has further highlighted the economic benefits of interregional transmission, particularly for accessing diverse renewable energy sources and improving overall energy availability.

For those reasons, integrated generation and transmission network expansion planning models have been proposed to ensure a reliable and resilient energy supply by simultaneously identifying the optimal timing, types, and locations for new generation units and transmission elements. The benefits of GTNEP can be summarized as follows [7]: (i) it allows the assessment of the interdependence that exists between the transmission network and the quality of renewable resources, (ii) it enables the integration of generation and transmission with other emerging technologies, (iii) it links the power system with electrical markets, and (iv) it results in improved expansion plans in terms of cost-effectiveness. On the other hand, power system constraints such as network flow limits, load demands, and reliability requirements link the two planning problems, introducing additional difficulty in finding feasible and practical planning solutions.

Two aspects must be considered to address the integrated GTNEP: (i) the mathematical modeling and (ii) the solution method. In the early stages of research aimed at addressing the GTNEP problem, the transport model of the transmission network was considered and consequently does not consider the Kirchhoff's Voltage Law (KVL) [8]. Subsequent studies [9], [10], [11] have adopted the use of the direct current (DC) model to address the GTNEP problem. Linearized AC models have also been applied to GTNEP, as in [12], [13], and [14]. The disadvantage of this linear approximation is the loss of model fidelity since it does not consider voltage variables, constraints related to reactive power limits, or the proper assessment of network power losses. Disregarding these factors means the model does not take into account essential aspects of power system operations that affect both the feasibility and economic efficiency of the solutions, resulting in sub-optimal expansion plans and underestimated investments, which are not very useful for real-world applications. Therefore, the expansion solutions derived from these approaches must be verified using a complete AC model to ensure they meet network security requirements. However, when the AC model is applied, it turns the GTNEP into a mixed-integer nonlinear programming problem, which is challenging to solve.

Regarding solution methods applied to GTNEP, the prevailing approach in most research is to employ linearized models solved by mathematical optimization-based methods [11], [15], [16]. However, mathematical-based solvers can only deal with linearized and convex models, which do not accurately represent network behavior. When mathematical optimization techniques are applied to non-convex models, they can deal only with a few variables, yielding unfeasible or no solutions for medium or large-scale networks. Therefore, when the full AC model is applied, meta-heuristic techniques have demonstrated their effectiveness and superiority over traditional optimization methods in TNEP, as proven in [17]. However, only some research works apply meta-heuristic techniques to solve the GTNEP. In [18], the Gradient-Genetic Hybrid algorithm was used to evaluate the impacts of wind and solar energy generation sources. In [19], the Genetic-Tabu Hybrid Algorithm was used to solve the GTNEP applied to planning energy systems in offshore oil fields.

Consequently, this study utilizes the AC model to address the operational challenges of GTNEP, providing a more comprehensive and realistic representation of the electrical system. As optimization techniques, the Iterated Greedy Algorithm (IGA) [20] and hybrid meta-heuristics based on differential evolution (DE) [21], Archimedes optimization algorithm (AOA) [22], and Honey Badger Algorithm (HBA) [23], along with the Tabu Search (TS) [24] meta-heuristic, were implemented to solve the GTNEP problem. It is worth noting that these methods have not yet been applied to the GTNEP problem. The full AC power flow model is adopted to study the impact of network power losses, reactive power compensation, and the long-term planning of new power plants and transmission lines. Reliability criteria such as Loss of Load Probability (LOLP) [25] are formulated as annual constraints to ensure reliable operation. Furthermore, a detailed breakdown of operational costs related to new power plants based on the levelized cost of electricity was considered in the model to facilitate cost-effective decision-making, which has not been thoroughly explored in other research works.

Thus, the contributions of this research are: (i) the use of nonlinear equations of the AC model to represent the transmission network which, different from state-of-art approaches, results in more realistic expansion plans, (ii) an integrated approach to generation and transmission network expansion planning, along with a comparative analysis against the sequential approach, (iii) the detailed breakdown of operational costs in the model, leading to more accurate decision-making, and (iv) the application and hybridization of different meta-heuristic algorithms to solve the GTNEP problem, along with a comparative analysis among them.

The remainder of this work is organized as follows: Section II presents the GTNEP mathematical model, while Section III describes the AOA-TS, DE-TS, HBA-TS, and IGA meta-heuristics implemented to solve the GTNEP problem. Finally, results and conclusions are shown in Section IV, and V respectively.

II. GTNEP MATHEMATICAL MODEL

The mathematical model of integrated GTNEP involves solving two problems: (i) the Master Problem (MP), which minimizes the investment cost of new power plants, including the cost obtained in the sub-problem, and (ii) the Sub-Problem (SP), which involves solving the TNEP problem.

A. MASTER PROBLEM

The master problem formulation comprises equations (1) to (10). These equations encompass the objective, constraints, and decision variables involved in the optimization process.

$$\min \ \upsilon = \varphi^{GIC} + \omega \tag{1}$$

$$\varphi^{GIC} = \sum_{i\in\Omega}\sum_{m\in\Lambda}\left(\varphi_m^{oc} + \varphi_m^{idc}\right)\cdot \overline{P}_i^m \cdot u_{mi} \tag{2}$$

$$\text{Subject to}: \ \underline{R}\cdot P^d \le \sum_{i\in\Omega}\left(\sum_{m\in\Lambda}\overline{P}_i^m \cdot u_{mi} + \overline{P}_i^g\right) \le \overline{R}\cdot P^d \tag{3}$$

$$\underline{R}\cdot Q^d \le \sum_{i\in\Omega}\left(\sum_{m\in\Lambda}\overline{Q}_i^m \cdot u_{mi} + \overline{Q}_i^g\right) \le \overline{R}\cdot Q^d \tag{4}$$

$$\sum_{i\in\Omega}\left(F_{fi}' + \sum_{m\in\Lambda} F_{fm}\cdot E_{mi}\cdot u_{mi}\right) \le \overline{F}_f \quad (\forall f \in \Upsilon) \tag{5}$$

$$\sum_{i\in\Omega}\left(P_{pi}' + \sum_{m\in\Lambda} P_{pm}\cdot E_{mi}\cdot u_{mi}\right) \le \overline{Y}_p \quad (\forall p \in \Psi) \tag{6}$$

$$\sum_{m\in\Lambda} u_{mi} \le 1 \quad (\forall i \in \Omega) \tag{7}$$

$$u_{mi} \in \{0,1\} \quad (\forall m \in \Lambda, \forall i \in \Omega) \tag{8}$$

$$LOLP \le \overline{LOLP} \tag{9}$$

$$LOLP = \sum_{\kappa\in\Delta} p_\kappa \cdot t_\kappa = \sum_{\kappa\in\Delta} P_\kappa \cdot (t_\kappa - t_{\kappa-1}) \tag{10}$$

In (1), the objective function aims to minimize the total generation investment cost defined in (2). The objective function also includes the investment and operational costs of the sub-problem ω defined in (11). Constraints (3) and (4) stipulate that the total active and reactive generation capacity from existing and candidate power plants must lie within the minimum $\left(\underline{R} = 1 + \underline{r}_{\%}\right)$ and maximum $\left(\overline{R} = 1 + \overline{r}_{\%}\right)$ percentage reserve margin of the total active and reactive power demand. This ensures that the system maintains adequate reserve capacity to handle fluctuations in demand and unexpected outages. Equation (5) specifies that the consumption of fuel type f must not exceed the maximum available fuel quantity $\overline{F}_f$, while (6) represents the amount of pollution type p that can be emitted. This quantity should not exceed the maximum limit $\overline{Y}_p$. Constraint (7) indicates that only one candidate power plant can be allocated to bus i, while (8) ensures that the decision to construct a generating unit is binary. Additionally, in (9), it is established that the Loss of Load Probability (LOLP) should not exceed the upper limit $\overline{LOLP}$. The LOLP is determined using (10), where p_κ, P_κ, and t_κ are computed using the forced outage rate (FOR) of each power plant, and a Load Duration Curve (LDC), following the process described in [26].

B. SUB-PROBLEM

The sub-problem involves solving the TNEP problem, which is further divided into two parts: (i) the expansion problem and (ii) the operational problem.

1) EXPANSION PROBLEM

The main objective of this problem, presented in (11), is to minimize the investment cost of adding new transmission lines, and reactive power compensation (12), the estimated cost of network power losses (13), and the estimated cost of energy production (16). The constraints for the expansion problem are related to the maximum number of lines that can be added to each right-of-way (14) and the integer nature of the added lines (15).

$$\min \ \omega = C_{exp} + C_{loss} + C_{op} \tag{11}$$

$$C_{exp} = \sum_{ij\in\Gamma} c_{ij}^L \cdot n_{ij} + \sum_{i\in\Omega}\varphi_i^q \cdot Q_i^c \tag{12}$$

$$C_{loss} = h \cdot f_{loss}\cdot \varphi^{loss}\cdot \sum_{ij\in\Gamma}\left(P_{ij}^{from} + P_{ij}^{to}\right) \tag{13}$$

$$\text{Subject to:} \ 0 \le n_{ij} \le \overline{n}_{ij} - n_{ij}^0 \quad (\forall i,j \in \Gamma) \tag{14}$$

$$n_{ij} \in \mathbb{Z} \quad (\forall i,j \in \Gamma) \tag{15}$$

2) OPERATIONAL PROBLEM

The operational problem provides, to the expansion problem, the cost of active load shedding and the estimated cost of energy production, as given in (16). To address this operational aspect, the AC optimal power flow is used. The objective function incorporates the Levelized Cost of Electricity (LCOE) [27], computed by equation (17) and the Capital Recovery Factor (18) associated with candidate power plants. The capital recovery factor helps determine the annualized cost of capital investment for each power plant, while the LCOE represents the minimum average price at which the electricity generated by the asset must be sold to break even at the end of its lifetime.

$$\min\, C_{op} = \frac{S^b}{10^6} \cdot \left(\sum_{i \in \Omega} \varphi_i^p \cdot P_i^c + \frac{h}{\zeta_m} \sum_{i \in \Omega} \varphi_i^{LCE} \cdot P_i^m \right) \quad (16)$$

$$\varphi_i^{LCE} = \sum_{m \in \Lambda} \psi_m \cdot \left(\frac{\zeta_m \cdot \varphi_m^{inv}}{h \cdot \psi_m} + \varphi_m^{FOM} + \varphi_m^{VOM} + {}^1/_{\eta_m} \cdot \varphi_m^{fuel} \cdot TF_m + {}^1/_{\eta_m} \cdot \varphi_m^{CO_2} \cdot TE_m \right) \quad (17)$$

$$\zeta_m = \frac{\alpha \cdot (1+\alpha)^{\chi_m}}{(1+\alpha)^{\chi_m} - 1} \quad (18)$$

$$\text{subject to: } P_i^g = \sum_{ij \in \Omega_l} P_{ij}^{from} + \sum_{ij \in \Omega_l} P_{ij}^{to} + g_i^{sh} V_i^2 + P_i^d - P_i^c - P_i^m \quad (\forall i \in \Omega) \quad (19)$$

$$Q_i^g = \sum_{ij \in \Omega_l} Q_{ij}^{from} + \sum_{ij \in \Omega_l} Q_{ij}^{to} - b_i^{sh} V_i^2 + Q_i^d - Q_i^c - Q_i^m \quad (\forall i \in \Omega) \quad (20)$$

$$\left(P_{ij}^{from}\right)^2 + \left(Q_{ij}^{from}\right)^2 \le \left(l_{ij} \cdot \overline{S}_{ij}\right)^2 \quad (\forall i,j \in \Gamma) \quad (21)$$

$$\left(P_{ij}^{to}\right)^2 + \left(Q_{ij}^{to}\right)^2 \le \left(l_{ij} \cdot \overline{S}_{ij}\right)^2 \quad (\forall i,j \in \Gamma) \quad (22)$$

$$v_{mi} \cdot \underline{P}_i^c \le P_i^c \le \overline{P}_i^c \cdot v_{mi} \quad (\forall m \in \Lambda,\ \forall i \in \Omega) \quad (23)$$

$$v_{mi} \cdot \underline{Q}_i^c \le Q_i^c \le \overline{Q}_i^c \cdot v_{mi} \quad (\forall m \in \Lambda,\ \forall i \in \Omega) \quad (24)$$

$$u_{mi} \cdot \underline{P}_i^m \le P_i^m \le \overline{P}_i^m \cdot u_{mi} \quad (\forall m \in \Lambda,\ \forall i \in \Omega) \quad (25)$$

$$u_{mi} \cdot \underline{Q}_i^m \le Q_i^m \le \overline{Q}_i^m \cdot u_{mi} \quad (\forall m \in \Lambda,\ \forall i \in \Omega) \quad (26)$$

$$\underline{P}_i \le P_i^g \le \overline{P}_i \quad (\forall i \in \Omega) \quad (27)$$

$$\underline{Q}_i \le Q_i^g \le \overline{Q}_i \quad (\forall i \in \Omega) \quad (28)$$

$$\underline{V}_i \le V_i \le \overline{V}_i \quad (\forall i \in \Omega) \quad (29)$$

$$-\frac{\pi}{2} \le \theta_i \le \frac{\pi}{2} \quad (\forall i \in \Omega) \quad (30)$$

The constraints for the operational problem are detailed from (19) to (30). Equation (19) addresses the active power balance at each bus of the system, while (20) deals with the reactive power balance. The limits of apparent power flow through the lines are represented by constraints (21) and (22), where $l_{ij} = n_{ij} + n_{ij}^0$. The set of constraints (23) - (26), represents the maximum and minimum capacities for active and reactive power generation, either by candidate or fictitious generators. The set of constraints (23) - (26), ensure that if power plant type m is allocated to load bus i, then the limits for active and reactive power generation of that bus will be determined by the parameters of the candidate generator. Otherwise, these values will be determined by the parameters of the fictitious generator. In (23) and (24) v_{mi} is defined as $v_{mi} = 1 - u_{mi}$. Constraints (27) - (30) represent the maximum and minimum limits for active power, reactive power, voltage magnitudes, and phase angles. Finally, the expressions for P_{ij}^{from}, P_{ij}^{to}, Q_{ij}^{from}, and Q_{ij}^{to} in equations (19) - (22) can be found in [28]. It is important to note that n_{ij} is specified as an integer variable, and u_{mi} is identified as a binary variable. Other variables are considered continuous unless explicitly specified otherwise.

3) LOAD SHEDDING STRATEGY

The active and reactive load shedding is modeled by incorporating fictitious generators allocated at the system load buses. Thus, if P_i^c is larger than zero or Q_i^c is different from zero, it indicates that the resulting transmission network configuration does not comply with the GTNEP sub-problem constraints. As a result, the following scenarios may occur [17]:

i. $P_i^c = 0$ indicates that there is no active power load shedding. This means that the fictitious generators do not generate active power.

ii. $P_i^c > 0$ indicates that there is active power load curtailment. One way to handle this situation is to consider the production cost of the fictitious generators φ_i^p as the cost associated with unserved energy, which implies that the final expansion plan may include load curtailments. Alternatively, another approach is to set φ_i^p to the same value as the cost of the most expensive transmission topology. Therefore, there is a penalty in the objective function to avoid the need for active load curtailments in the final expansion plan. The penalization to the objective function guarantees that $P_i^c = 0$.

iii. $Q_i^c = 0$ indicates that there is no reactive power load shedding. This means that the fictitious generators do not generate reactive power.

iv. $Q_i^c \neq 0$ indicates that there is reactive power load curtailment or, in other words, the system requires the allocation of reactive power compensation. In this context, it is essential to ensure that the compensation cost is always positive, meaning that the term φ_i^q must be larger than zero ($\varphi_i^q > 0$) for capacitive compensation and less than zero ($\varphi_i^q < 0$) for inductive compensation. In this work, the reactive load supplied by these fictitious generators is considered the reactive power compensation that must be added to the load buses to maintain system stability and achieve feasible economic expansion plans.

III. META-HEURISTICS IMPLEMENTATION

In this work, it was implemented the Iterated Greedy Algorithm (IGA) [20] to address the sub-problem. For the master problem, it was applied four population-based hybrid meta-heuristics and conducted a comparative analysis of their efficiency. The meta-heuristics employed include Differential Evolution (DE) [21], the Archimedes Optimization Algorithm (AOA) [22], and the Honey Badger Algorithm (HBA) 23, each hybridized with Tabu Search (TS) [24], resulting in DE-TS, AOA-TS, and HBA-TS, respectively. Additionally, we introduced a variant of HBA-TS incorporating Levy flights (HBA-TS-LF) [29]. These meta-heuristics were selected based on the claims by the authors of AOA and HBA, which suggest that these algorithms outperform several well-known state-of-the-art and recently introduced meta-heuristics, as evidenced in [22] and 23, respectively.

Figure 1 shows the flow chart of the HBA-TS meta-heuristic, which will be used to describe how meta-heuristics are applied to the AC-GTNEP.

A. TEST SYSTEM DATA

This work used three test systems to evaluate the AC-GTNEP, the Garver 6-bus, the IEEE 24-bus, and the IEEE 118-bus test systems.

B. AC-GTNEP PARAMETERS

In this step, the parameters of the AC-GTNEP corresponding to the mathematical model in Section II and defined in the nomenclature need to be initialized.

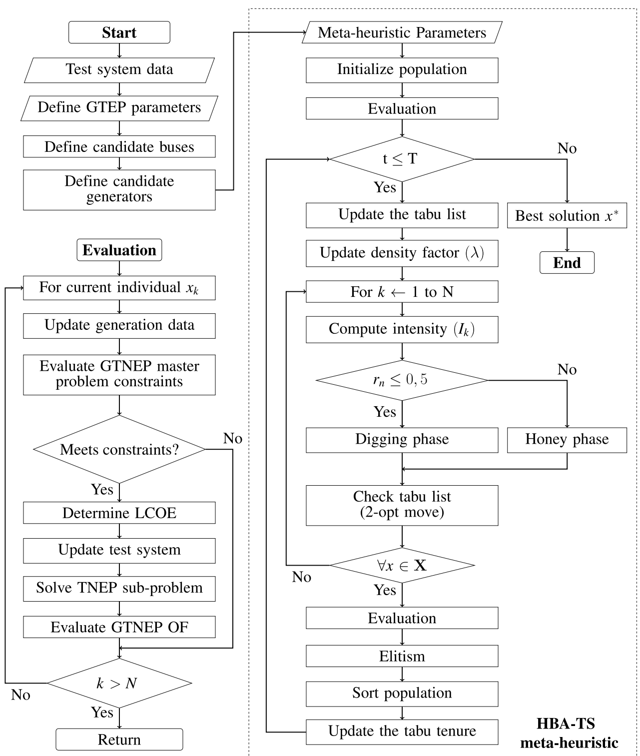

FIGURE 1. Proposed HBA-TS hybrid meta-heuristic applied to the AC-GTNEP problem.

C. CANDIDATE BUSES

Load nodes are selected as candidate nodes to allocate new power plants. These candidate load nodes are arranged in a vector format, which will be considered an individual x_k of the population X in the master problem. The number of individuals N (population size) is defined as a common parameter for all meta-heuristics, and the number of load nodes is defined as the dimension D (number of elements of each individual) of the master problem.

D. CANDIDATE POWER PLANTS

Determining the candidate power plants and their respective parameters is essential to computing the levelized cost of electricity. These parameters are provided in Tables 1 and 2. These tables offer comprehensive information regarding the characteristics of conventional and non-conventional power plants considered in the study. This detailed information serves as the basis for evaluating the economic viability and performance of different types of power generation technologies within the integrated planning framework.

E. META-HEURISTICS PARAMETERS

For each meta-heuristic, specific parameters must be determined through a trial-and-error process. These parameters were set using the Garver 6-bus test system and applied consistently across all tests. Table 3 describes the recommended parameter settings for the meta-heuristics used in this study.

F. INITIAL POPULATION

The population X for the master problem is initialized by randomly generating a set of solutions corresponding to the number of available candidate power plants. Each individual x_k in the population is formed by D elements, where each row corresponds to a load bus in the test system, and each element represents a candidate power plant.

G. EVALUATION

In this step, the initial population is evaluated. As depicted in Figure 1, the evaluation process involves updating each individual's test system generation data and assessing the master problem constraints. If these constraints are met, the levelized cost of electricity is computed, and the test system data is updated. With the updated data, the sub-problem is solved using the IGA algorithm [20]. Finally, the objective function of the master problem is evaluated. If all individuals have been assessed, the process returns to the meta-heuristic, where the optimization process of the master problem continues until the termination criterion is met.

1) SUB-PROBLEM OPTIMIZATION IGA

In the evaluation process for each individual, the TNEP sub-problem is solved using the IGA meta-heuristic. Details and settings for this IGA approach can be found in [20]. The IGA employs a greedy constructive heuristic algorithm, which builds a solution step-by-step, starting from an empty solution S^0. An element is added at each step until a complete solution S^* is generated. The IGA structure is defined by five main stages: initialization, destruction, construction, acceptance criterion, and stopping criterion, each described below.

(i) Initialization: This phase starts with an empty solution S^0 and adds one transmission line in each corridor at a time. For each of these added lines, the constraints and objective function of the sub-problem are evaluated. Once a line has been added to all corridors, the one that produced the lowest value in the objective function is added to the solution. This procedure continues until the maximum number of iterations is reached. If adding more transmission lines does not improve the objective function value, it means that the final solution S^* has been found.

(ii) Destruction: In this phase, r elements are removed from the incumbent solution S^*. The value of r is determined based on the percentage of minimum and maximum values $\left[\underline{\pi}, \overline{\pi}\right]$ of the total added lines, and the number of steps (δ) of possible combinations of r line elements.

(iii) Re-construction: Starting from the destructed solution, the same process as the initialization phase is repeated until a final solution is constructed.

(iv) Acceptance criterion: The element that produces the lowest value in the objective function will be added to the solution.

(v) Stopping criterion: Maximum number of iterations T.

H. MASTER PROBLEM OPTIMIZATION

After evaluating the initial population, the logic of the specific population-based meta-heuristic is applied iteratively until a maximum number of iterations T is achieved (see Figure 1). A brief description of the population-based meta-heuristics used in this work is presented below.

1) HONEY BADGER ALGORITHM (HBA)

The proposed algorithm is inspired by the intelligent foraging behavior of the honey badger, creating an efficient search strategy for optimization problems. The dynamic search behaviors, including digging and honey-finding phases, are translated into HBA's exploration and exploitation phases. Figure 1 illustrates the optimization process that integrates the HBA-TS algorithm, while a complete mathematical formulation can be found in [23]. The following process continues until a maximum number of iterations is reached:

(i) Tabu list (create/update): After the evaluation process, a tabu list (TL) is created or updated to store the current incumbent solution. This list is filled and emptied as the algorithm progresses based on the tabu tenure (TT).

(ii) Density factor λ: The density factor determines the extent to which the search behavior varies over time, with a decreasing value encouraging more exploitation as iterations progress.

$$\lambda = C_\lambda \cdot exp\left(-\frac{t}{T}\right) \tag{31}$$

(iii) Intensity (I_k): Represents the degree of focus or concentration of a honey badger towards a potential solution. It is determined by both the attractiveness of the solution area $S_k = (x_k - x_{k+1})^2$ and the proximity of the honey badger to the prey $d_k = x^* - x_k$.

$$I_k = r_n \cdot \frac{S_k}{4 \cdot \pi \cdot d_k^2} \tag{32}$$

(iv) Digging phase: During this phase, honey badgers rely on scent intensity (I_k), distance to prey (d_k), dynamic search behavior influenced by time (λ), disturbances (F), and random numbers (r_n) to explore and locate even better solutions.

$$\begin{aligned} x_k^{t+1} &= x^* + F \cdot C_\beta \cdot I_k \cdot x^* + F \cdot r_n' \cdot \lambda \cdot d_k \\ &\quad \cdot \left|cos\left(2\pi r_n\right) \cdot \left(1 - cos\left(2\pi r_n\right)\right)\right| \end{aligned} \tag{33}$$

(v) Honey phase: In this phase, new individuals x_k^{t+1} move towards the best current solution x^*.

$$x_k^{t+1} = x^* + F \cdot r_n' \cdot \lambda \cdot d_k \tag{34}$$

(vi) Tabu list/ 2-opt move: Each individual x_k in the modified population X^{t+1} is evaluated after the digging and honey phases. If it is found in the tabu list, a 2-opt move [30] is executed to modify the individual.

(vii) Finally, the new population X^{t+1} is evaluated and sorted, the best individuals are stored (Elitism), and the tabu tenure of all elements in the tabu list is updated.

2) LÉVY FLIGHT

The concept of Lévy flight, inspired by the foraging behavior of some animal species such as birds and insects, has been incorporated into the Honey Badger algorithm [31]. Lévy flights are characterized by long-range and random movements, allowing individuals to escape from local optima and explore distant areas in the search space. It consists in generating steps from a Levy distribution that replace the random numbers denoted by r_n' in (33) and (34) by:

$$r_n' = s \cdot \frac{\sigma_u}{\sigma_v} \tag{35}$$

where the values of s, σ_u, and σ_v are computed as follows:

$$s = \frac{u}{v^{1/\beta}} \tag{36}$$

$$u \sim N\left(0, \sigma_u^2\right), \quad v \sim N\left(0, \sigma_v^2\right) \tag{37}$$

$$\sigma_u = \left(\frac{\Gamma\left(1+\beta\right) \cdot \sin\left(\frac{\pi \cdot \beta}{2}\right)}{\Gamma\left(\left(1+\frac{\beta}{2}\right) \cdot \beta \cdot 2^{(\beta-1)/2}\right)}\right)^{1/\beta}, \quad \sigma_v = 1 \tag{38}$$

3) ARCHIMEDES OPTIMIZATION ALGORITHM

The Archimedes Optimization Algorithm (AOA) is an optimization method inspired by the Archimedes principle of physics, where objects (x_k) immersed in a fluid experience an upward buoyant force equal to the weight of the displaced fluid. AOA utilizes this principle to iteratively optimize solutions by updating individual properties like volume, density, and acceleration based on interactions with neighbor objects; detailed mathematical formulation and pseudocode of AOA can be found in [22]. The main steps for AOA are as follows:

(i) Initialization: During the initialization phase, the population, density, acceleration, and volume are randomly generated.

(ii) Evaluation: The initial population is evaluated as in the case of HBA-TS algorithm (Figure 1).

(iii) Main loop of AOA-TS: During the optimization process, until a maximum number of iterations is reached, the algorithm creates/updates the tabu list. It then updates the features of all individuals, computing a transfer factor. If this factor is 0.5 or less, the algorithm enters the exploration phase; otherwise, it proceeds to the exploitation phase. Following this, the tabu list is checked for the modified population, and if necessary, a 2-opt move is executed.

(iv) Finally, the new population is evaluated and sorted, the best individuals are stored (Elitism), and the tabu tenure of all elements in the tabu list is updated.

4) DIFFERENTIAL EVOLUTION

The DE-TS structure is defined in four mains mechanics, such as initialization, mutation, recombination, and selection. These mechanics have been designed to implement the DE/rand/1/bin variation [21].

(i) Initialization: The population X is randomly generated during the initialization phase.

(ii) Evaluation: In this phase, each individual in the population is evaluated based on data from candidate power plants.

(iii) Main loop of DE-TS: During the optimization process, until a maximum number of iterations is reached, the algorithm creates/updates the tabu list. After that, the mutation and recombination process is performed. If the new vector is in the tabu list, a 2-opt move is executed to modify the individual, which is then evaluated. Finally, the best individual is selected, and the tabu tenure of all vectors in the tabu list is reduced. This process is carried out for all individual x_k in the population X.

(iv) At the end of each iteration, the best individuals are stored, and the population is sorted so that the next iteration is started.

IV. TEST AND RESULTS

This research work evaluates the proposed methodology using three test systems: the Garver 6-bus system, the IEEE 24-bus system, and the IEEE 118-bus system. The problem was implemented using the Julia programming language [32], running on an Intel i7 processor at 3.60 GHz with 16GB of RAM. The operational problem described in section II-B2 was solved using IPOPT. The results include information about the added lines, new power plants that need to be incorporated, the requirements of reactive power compensation, network power losses, and their respective costs. The energy cost of projected power plants during their lifetime is also considered.

TABLE 1. Technical and economic characteristics of conventional generation.

Technology Type	Coal (Lignite)-A	Natural Gas (CCGT)-B	Natural Gas (OCGT)-C
Active power capacity (MW)	600	500	600
Reactive power capacity (MVA)	100	45	48
Overnight Cost (USD/kW)	2189.486	957.900	738.952
Fixed O&M Costs (USD/MWh)	8.6	13.31	16.71
Variable O&M Costs (USD/MWh)	3.2	2.31	2.00
Coal Price (USD/ton)	51	NR	NR
Natural Gas Price (USD/MBtu)	NR	3.2	3.2
Carbon Price (USD/ton of CO_2)	30	30	30
Calorific Value (kcal/kg)	4063.6	NR	NR
CO_2 Emission Factor (tons/TJ)	101.00	56.10	56.10
Efficiency (%)	34	58	44
Capacity Factor (%)	85	85	44
Lifetime (years)	40	30	30
FOR (%)	6.0	9.0	7.0
Construction Years	4.0	3.0	2.0

NR: not required for the power plant.

TABLE 2. Technical and economic characteristics of renewable generation.

Technology Type	Solar (PV) D	Onshore wind E
Active power capacity (MW)	100	100
Reactive power capacity (MVA)	10	10
Overnight Cost (USD/kW)	1197.4	1314.7
Fixed O&M Costs (USD/MWh)	6.48	5.98
Variable O&M Costs (USD/MWh)	0	0.02
Capacity Factor (%)	31	47
Lifetime (years)	25	25
FOR (%)	6.0	5.0
Construction Years	1.0	1.0

A. PARAMETERS OF CANDIDATE POWER PLANTS

In [33], the distribution of global energy production across different technologies reveals that 61% of total energy generation stems from unabated fossil fuels. In contrast, renewable energy sources contribute 29% to the total energy output. Therefore, generation plants based on these energy sources were considered as candidates for power plants, including a coal-fired thermal power plant, a Combined Cycle Gas Turbine (CCGT) power plant, an Open Cycle Gas Turbine (OCGT) power plant, a solar photovoltaic (PV), and an onshore wind power plant. Tables 1 and 2 present technical and economic characteristics of candidate power plants considered in this research [27]. The CO_2 emission factors for different types of fuels can be found in [34].

B. GENERAL PARAMETERS

The following data were assumed for all tests: $\alpha = 10\%$, $h = 8760$. The maximum limit for reactive power sources was considered to be $\overline{Q}^c_{(i)} = 50$ MVar, and the cost $\varphi^q_{(i)}$ was 0.025 MUSD per each MVar. The voltage magnitude limits were $V^{max} = 1.05$ p.u. and $V^{min} = 0.95$ p.u. The maximum active power limit for the fictitious generators was considered to be $\overline{P}^c_{(i)} = 1000$ MW. However, the cost $\varphi^p_{(i)}$ was considered to be high, aiming to achieve an expansion plan where active load shedding is approximately zero, $P^c_{(i)} \approx 0$. For network power losses $\varphi^{loss} = 100$ USD/MWh, and $f_{loss} = 0.6144$. In the conducted tests, no consideration was given to the maximum fuel limits or CO_2 emissions limits. Furthermore, operation and maintenance costs for existing generation units were not considered in the analysis for the Garver 6-bus and IEEE 24-bus systems. However, for the IEEE 118-bus system, these costs were included in the analysis. A modified load duration curve was used to determine the loss of load probability as defined in (39).

$$P^d_{norm} = 1 - 0.83 \cdot (t_d) + 4.73 \cdot (t_d)^2 - 13.54 \cdot (t_d)^3 + 15.72 \cdot (t_d)^4 - 6.43 \cdot (t_d)^5 \quad (39)$$

C. PARAMETERS OF META-HEURISTICS

The meta-heuristics used in this research work include the hybrid meta-heuristic AOA-TS, DE-TS, HBA-TS, HBA-TS-LF, and IGA. Table 3 defines the parameters used in the optimization process for each proposed meta-heuristic.

D. GARVER 6-BUS SYSTEM

The Garver system comprises six buses with a total active power demand of 760 MW and 152 Mvar of reactive power. Additionally, it includes 15 candidate right-of-ways for new transmission lines.The installed active power capacity is 1140 MW, while the reactive power capacity ranges between −30 Mvar and 332 Mvar. The maximum number of lines that can be added to each right-of-way, denoted as $\overline{n}$, is set to 5. This system consists of three load buses that are considered potential locations for allocating candidate power plants. Thus, results for three case studies, denoted as A1, A2, and A3, are presented in Table 4, and the performance of the applied meta-heuristics is detailed in Tables 5, 6, and 7.

TABLE 3. Parameter configurations of the selected algorithms.

Algorithm	Parameters
DE	Population size = 50, scale factor = 0.5 Recombination probability = 0.7
AOA	Number of objects = 50 $C_1 = 0.2$ $C_2 = 6$, $C_3 = 1.5$ $C_4 = 0.5$
HBA	Number of honey badgers = 50 , $C_\lambda = 2$, $C_\beta = 6$
IGA	$\underline{\pi} = 10\%$, $\overline{\pi} = 30\%$, $\delta = 3$
TS	Tabu tenure is set to 40% of the allowed iterations.
LF	$\beta = 1.5$

1) CASE STUDY A1

In this case, two scenarios are explored: scenario A1.1, which does not include the allocation of reactive power, and scenario A1.2, which considers including reactive power sources in its formulation. In both scenarios, power plants A (coal-lignite), B (CCGT), D (Solar PV), and E (Onshore wind) were considered as candidate options, while constraints related to minimum and maximum reserve margin and LOLP were not considered. The results presented in Table 4 for scenarios A1.1 and A1.2 correspond to the integrated generation and transmission network expansion planning. There is no need to add new power plants in scenarios A1.1 or A1.2, as the existing generation has a reserve margin of 50%. Therefore, this case study corresponds to the TNEP problem, and the results are consistent with [35] and [36]. From the results, it is observed that scenario A1.2 achieves a total savings of 47.43 MUSD (28.46%), primarily due to reactive power compensation $\left(Q^c_5 = 49, 43 \text{ Mvar}\right)$, which leads to the requirement of fewer transmission lines in the corridors $(2-6)$ and $(3-5)$, compared to scenario A1.1.

Regarding the performance of the meta-heuristics, Table 5 presents various indicators, such as the number of objective function evaluations for the master problem and the sub-problem, as well as the execution time for each scenario. For this scenario, DE-TS takes 7.6 hours to reach ten iterations, which is almost 5 times longer than the time taken by HBA-TS and AOA-TS in scenario A1.1, and almost two times longer in scenario A1.2. This suggests that this meta-heuristic is not as efficient as the others applied in this study, at least in terms of computational time.

2) CASE STUDY A2

In case study A2, 100 MW was added to each existing load, and power plants A, B, and C were simultaneously considered as candidate options. For this scenario, the planning of reactive power source allocation was not considered, nor was the loss of load probability. The minimum and maximum reserve margins were set as 20% and 40% of the total demand, respectively. Thus, scenario A2.1 addresses the integrated GTNEP, while scenario A2.2 deals with the sequential study of GEP and then TNEP. The expansion plans are presented in Table 4, while the performance of the applied meta-heuristics is detailed in Table 6. The results show that integrated planning achieved a cost saving of 168.14 MUSD (11.30%) in the final expansion plan, with the type C power plant being implemented at bus 5 ($u_{C,5} = 1$), and the following transmission lines added: $n_{2-3} = 1$, $n_{2-6} = 2$, and $n_{4-6} = 3$. The cost savings amount to 127 MUSD (42.76%) related to new transmission lines, 40.47 MUSD (5.87%) in the estimated energy cost of the new power plants, and 0.67 MUSD (5.46%) in network power losses costs.

3) CASE STUDY A3

In this case study, similar to scenario A2, 100 MW was added to each load. However, the difference lies in considering power plants A, B, C, D, and E simultaneously as candidate options. In this context, scenario A3.1 addresses integrated generation and transmission network expansion planning, while scenario A3.2 deals with sequential GEP and TNEP studies, considering, in both cases, the allocation of reactive power sources. The maximum loss of load probability value for this scenario was set to 2%, while the minimum and

TABLE 4. Results for integrated generation and transmission network expansion planning. Garver 6-bus system.

Scenario	A1.1	A1.2	A2.1	A2.2	A3.1	A3.2
Added lines	$n_{2-6}=2$ $n_{3-5}=2$ $n_{4-6}=2$	$n_{2-6}=1$ $n_{3-5}=1$ $n_{4-6}=2$	$n_{2-3}=1$ $n_{2-6}=2$ $n_{4-6}=3$	$n_{2-6}=3$ $n_{3-5}=1$ $n_{5-6}=3$	$n_{2-6}=3$ $n_{3-5}=2$ $n_{4-6}=3$	$n_{2-6}=4$ $n_{3-5}=1$ $n_{4-6}=3$
Power plants required	-	-	$u_{C,5}=1$	$u_{C,4}=1$	$u_{B,2}=1$ $u_{D,5}=1$	$u_{B,4}=1$ $u_{D,5}=1$
Shunt compensation (MVar)	-	$Q_5^c=49.43$	-	-	0.0	0.0
Estimated power losses (MW)	12.41	14.88	21.55	22.80	22.34	21.49
Line cost (MUSD)	160	110	170	297	220	230
Shunt compensation cost (MUSD)	-	1.24	-	-	0.0	0.0
Power losses cost (MUSD)	6.68	8.01	11.60	12.27	12.03	11.56
Generation investment cost (MUSD)	-	-	488.82	488.82	680.17	680.17
Estimated energy cost (MUSD)	-	-	648.63	689.10	322.09	318.43
Total cost (MUSD)	166.68	119.25	1319.05	1487.19	1234.28	1240.16
Power losses	Yes	Yes	Yes	Yes	Yes	Yes
Reactive power compensation	No	Yes	No	No	Yes	Yes

TABLE 5. Meta-heuristics performance applied to AC-GTNEP. Garver 6-bus system, case study A1 with 50 individuals and 10 iterations.

Meta-heuristic	HBA-TS-LF		HBA-TS		AOA-TS		DE-TS	
Scenario	A1.1	A1.2	A1.1	A1.2	A1.1	A1.2	A1.1	A1.2
O.F. evaluations (SP)	100913	164576	133777	120947	126196	113636	196547	151798
O.F. evaluations (MP)	144	251	198	188	170	161	259	224
Computational time (h)	1.2	2.1	1.6	1.6	1.5	1.5	7.6	3.3

TABLE 6. Meta-heuristics performance applied to AC-GTNEP. Garver 6-bus system, case study A2 with 50 individuals and 10 iterations.

Meta-heuristic	HBA-TS-LF		HBA-TS		AOA-TS		DE-TS	
Scenario	A2.1	A2.2	A2.1	A2.2	A2.1	A2.2	A2.1	A2.2
O.F. evaluations (SP)	310670	1284	172497	1284	147354	1284	200749	1503
O.F. evaluations (MP)	123	341	85	330	70	336	131	385
Computational time (h)	3.9	0.1	2.3	0.1	2.0	0.1	3.7	1.6

TABLE 7. Meta-heuristics performance applied to AC-GTNEP. Garver 6-bus system, case study A3 with 50 individuals and 10 iterations.

Meta-heuristic	HBA-TS-LF		HBA-TS		AOA-TS		DE-TS	
Scenario	A3.1	A3.2	A3.1	A3.2	A3.1	A3.2	A3.1	A3.2
O.F. evaluations (SP)	252090	1980	147292	1959	100507	1927	227813	1314
O.F. evaluations (MP)	128	489	82	402	62	392	135	401
Computational time (h)	2.9	0.05	1.4	0.1	1.2	0.05	3.8	1.1

maximum reserve margins were set to 20% and 40% of the total demand, respectively. Power plants B and D must be installed for this case study. Scenario A3.1 shows that integrated planning leads to a transmission expansion plan with the same number of added lines but with a lower cost than sequential planning in scenario A3.2. As a result, a total savings of 5.88 MUSD (0.47%) was achieved with integrated planning in scenario A3.1, primarily attributed to the lower cost of expanding the transmission system. For this scenario, the cost savings amount to 10 MUSD (4.35%) related to new transmission lines, while there is an increased cost of 3.66 MUSD (1.15%) in the estimated energy cost of the new power plants and 0.47 MUSD (3.9%) in network power losses costs. The performance of the applied meta-heuristics is detailed in Table 7.

In all case studies of the Garver system, all meta-heuristics converged to the minimum value in less than 10 iterations. Among them, HBA-TS and DE-TS stand out for achieving this solution in few iterations as illustrated in Figure 2. According to the results presented in Tables 5, 6, and 7, DE-TS requires a higher number of objective function evaluations for both the master problem and the sub-problem, resulting in longer computational times. This issue is due to the encoding method used in the DE/rand/1/bin variation, where individuals in the population are evaluated one at a time, demanding calls to subroutines developed for each of them. In contrast, meta-heuristics like HBA-TS evaluate the entire population within the same subroutine, eliminating the need for repeated calls to other parts of the code.

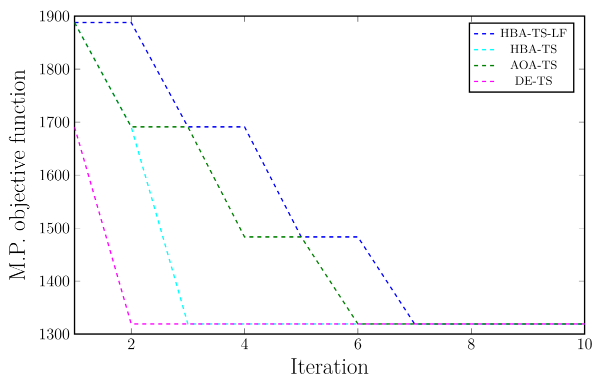

FIGURE 2. Convergence process of the HBA-TS-LF, HBA-TS, AOA-TS, and DE-TS meta-heuristics for scenario A2.1 with 50 individuals.

TABLE 8. Results for integrated generation and transmission network expansion planning. IEEE 24-bus system.

Scenario	B1.1	B1.2	B2.1	B2.2
Added lines	$n_{7-8}=1$ $n_{6-10}=1$ $n_{14-16}=1$	$n_{2-6}=3$ $n_{3-5}=3$ $n_{5-6}=1$	$n_{6-10}=2$ $n_{7-8}=2$ $n_{14-16}=1$ $n_{16-17}=1$	$n_{1-5}=1, n_{2-24}=1,$ $n_{6-10}=2, n_{7-8}=2,$ $n_{14-23}=1, n_{15-24}=1$ $n_{16-17}=1$
Power plants required	-	-	$u_{C,10}=1$	$u_{C,19}=1$
Shunt Comp. (MVar)	830.51	-	801.64	823.72
Power losses (MW)	257.12	221.77	294,26	293.27
Line cost (MUSD)	86	424	154	330
Shunt comp. cost (MUSD)	20.76	-	20.04	20.59
Power losses cost (MUSD)	138.39	119.36	158.37	157.84
Generation investment cost (MUSD)	-	-	488.82	488.82
Estimated energy cost (MUSD)	-	-	968.20	965.34
Total cost (MUSD)	245.15	543.36	1789.43	1962.59
O.F. evaluation (SP)	861	9512	-	-
O.F. evaluation (MP)	1	1	-	-
Computational time (h)	0.05	1.11	-	-
Power losses	Yes	Yes	Yes	Yes
Reactive power compensation	Yes	No	Yes	Yes

TABLE 9. Meta-heuristics performance applied to AC-GTNEP. IEEE 24-bus system, case study B2 with 50 individuals and 10 iterations.

Meta-heuristic	HBA-TS-LF		HBA-TS		AOA-TS		DE-TS	
Scenario	B2.1	B2.2	B2.1	B2.2	B2.1	B2.2	B2.1	B2.2
O.F. evaluations (SP)	352120	4751	226820	1536	441761	2459	689159	4455
O.F. evaluations (MP)	88	107	56	78	112	86	131	165
Computational time (h)	20.5	0.49	13.23	0.48	25.14	0.52	40.08	0.99

The results for the Garver system reveal that even when the type C power plant is the most economical option among those that use fuel such as coal or natural gas to produce energy, as evidenced in scenario A2, in scenario A3, it was crucial to incorporate plants B and D to meet the constraints of loss of load probability and maximum reserve margin, highlighting the importance of diversifying energy sources. This adjustment led to a lower cost for case study A3 compared to case study A2 (6.4% and 16.4% for each scenario, respectively), mainly attributed to the reduced energy costs resulting from the implementation of the solar photovoltaic plant, highlighting the economic benefits of renewable energy sources.

E. IEEE 24-BUS SYSTEM

The data for the IEEE 24-bus system can be found in [36]. This system has a total demand of 8550 MW and 1740 Mvar, with an installed capacity of active power of 10215 MW and an installed capacity of reactive power ranging between −1905 Mvar and 7328 Mvar. There are 41 candidate corridors for adding new transmission lines. The maximum number of lines that can be added to each corridor was set to 5. In all case studies involving the IEEE 24-bus system, the loss of load probability constraint was not considered, and the minimum and maximum reserve margins were set at 5% and 20% of the total demand, respectively. The expansion plans for this system are presented in Table 8.

1) CASE STUDY B1

Case study B1 refers to the base case of the IEEE 24-bus system, and two scenarios are analyzed. The first scenario, B1.1, considers the allocation of reactive power sources. The second scenario, B1.2, does not include allocating reactive power sources. In this case study, the installed capacity of active power exceeds the demand by 20%. Given this scenario, the base case was evaluated using the HBA-TS algorithm, assuming no need to add new power plants. Therefore, this case study corresponds to the TNEP problem, and the results are consistent with those presented in [36].

From the results presented in Table 8, it is shown that a saving of 298.21 MUSD (54.9%) was achieved for the scenario considering the joint planning of transmission lines and allocation of reactive power sources (scenario B1.1), compared to the case considering only the addition of transmission lines. This saving is attributed to the construction of fewer transmission lines, primarily due to the allocation of reactive power sources at bus 3 $\left(Q_3^c = 293.19\right)$ and bus 9 $\left(Q_9^c = 537.31\right)$. Scenario B1.2 requires more objective function evaluations in the sub-problem, consequently increasing the computational time required for the optimization process (see Table 8).

2) CASE STUDY B2

For scenario B2, the generation and demand data were modified. The modified system includes the addition of 50 MW of additional demand at each existing load. Additionally, there was a reduction in the maximum generation capacity of units allocated at buses 13 (−200 MW), 15 (−100 MW), 16 (−100 MW), 18 (−300 MW), and 21 (−200 MW), and reactive power sources were allocated at buses 3 and 9. For this scenario, the generation units listed in Tables 1 and 2 were simultaneously considered as candidate options.

TABLE 10. Results for integrated generation and transmission network expansion planning. IEEE 118-bus system.

Scenario	C1.1	C1.2	C2.1	C2.2
Added lines	$n_{3-5}=1, n_{8-9}=1,$ $n_{8-5}=2, n_{9-10}=1,$ $n_{26-30}=2, n_{23-32}=1,$ $n_{38-37}=2, n_{77-78}=1,$ $n_{82-83}=1, n_{94-100}=1,$ $n_{17-113}=1$	$n_{3-5}=1, n_{8-9}=1,$ $n_{8-5}=2, n_{9-10}=1,$ $n_{26-30}=2, n_{23-32}=1,$ $n_{38-37}=2, n_{82-83}=1,$ $n_{93-94}=1, n_{17-113}=1$	$n_{3-5}=1, n_{8-9}=1,$ $n_{8-5}=2, n_{9-10}=1,$ $n_{26-30}=2, n_{23-32}=1,$ $n_{38-37}=1, n_{82-83}=1,$ $n_{93-94}=1, n_{17-113}=1$	$n_{3-5}=1, n_{8-9}=2,$ $n_{8-5}=2, n_{9-10}=1,$ $n_{15-17}=1, n_{23-15}=1,$ $n_{26-30}=1, n_{23-32}=1,$ $n_{77-78}=1, n_{82-83}=1,$ $n_{94-100}=1, n_{17-113}=1$
Power plants required	-	-	$u_{C,52}=1$	$u_{C,33}=1$
Shunt Comp. (MVar)	-	-	-	-
Estimated power losses (MW)	104.77	111.64	122.13	116.45
Line cost (MUSD)	126.6	126.6	119.8	125.3
Shunt comp. cost (MUSD)	-	-	-	-
Power losses cost (MUSD)	56.39	60.09	65.73	62.68
Generation investment cost (MUSD)	-	-	488.82	488.82
Estimated energy cost (MUSD)	0.0	0.0	598.18	591.75
Estimated cost of existing energy (MUSD)	-	26687.48	23 814.86	24 453.85
Total cost (MUSD)	182.99	26874.17	25089.72	25 722.47
O.F. evalutaions (SP)	177768	198541	89684	5394
O.F. evalutaions (MP)	22.00	28.00	23.00	28.00
Computational time (h)	38.15	47.15	46.30	1.64
Power losses	Yes	Yes	Yes	Yes
Reactive power compensation	No	No	No	No

Table 8 presents the results for scenario B2, covering both the integrated GTNEP problem (B2.1) and the sequential GEP-TNEP problem (B2.2).

The results indicate that in both scenarios, the implementation of power plant type C is necessary. In this way, the expansion plan in scenario B2.1 achieved a savings of 173.16 MUSD (8.82%), highlighting the efficiency of integrated GTNEP. This integrated approach resulted in a more cost-effective solution than the sequential scenario B2.2. The cost savings for the integrated GTNEP amount to 176 MUSD (53.33%) related to new transmission lines and 0.55 MUSD (2.67%) in reactive power allocation, while there is an increased cost of 2.86 MUSD (0.29%) in the estimated energy cost of the new power plants and 0.53 MUSD (0.33%) in network power losses costs.

For this case study, Table 9 presents the performance of the meta-heuristics, all of which reached the same solution that minimizes the objective function. However, HBA-TS stands out as the most efficient in terms of computational time, being three times faster than DE-TS, which took 40.08 hours to reach ten iterations. This result indicates that not only did HBA-TS achieve faster convergence, but it also required fewer objective function evaluations compared to DE-TS.

F. IEEE 118-BUS SYSTEM

This system has 118 buses, 186 corridors to add new transmission lines, 91 load buses, and 54 thermal generation units. The active and reactive power demand is 6240 MW and 2470 MVar, respectively, with an installed capacity of 7170 MW of active power [17]. In the tests, the HBA-TS meta-heuristic was employed in the optimization process of the master problem. Two case studies were analyzed, where the type C power plant was considered a candidate option, and ten load buses were evaluated as potential locations for its allocation. These load buses were 3, 5, 11, 20, 33, 41, 52, 86, 94, and 108. Additionally, the allocation of reactive power sources and the loss of load probability were not considered in any of the mentioned cases. Besides this, 17 corridors were considered for adding new transmission lines: 3-5, 8-9, 8-5, 9-10, 15-17, 23-15, 25-27, 26-30, 23-32, 38-37, 77-78, 82-83, 93-94, 94-100, 99-100, 17-113, and 12-117, with a maximum of 2 transmission lines that can be added to each corridor. Finally, the number of iterations for the master problem was set to 2. Results for the integrated GTNEP are presented in Table 10.

1) CASE STUDY C1

For this case study, two scenarios were considered. Scenario C1.1 corresponds to the base case without considering the energy cost of existing power plants, while scenario C1.2 considers the base case but includes the cost of existing generation units. In both scenarios, reserve margin constraints were not considered, aiming for this case study to be considered a TNEP problem. As evidenced in Table 10, the results indicate that the cost of adding new transmission lines is the same for both scenarios, 126.6 MUSD, although they present different topologies. It is also noteworthy that adding the proposed power plant is unnecessary.

2) CASE STUDY C2

This case study begins with scenario C1.2, which considers the energy generation cost of existing power plants. In scenario C2.1, an integrated GTNEP is conducted, while scenario C2.2 involves sequential GEP-TNEP planning. For both scenarios, the minimum and maximum reserve margins were set at 15% and 30%, respectively. Table 10 presents the results for these scenarios, showing a total cost saving of 635.01 MUSD (2.47%) in scenario C2.1. The cost savings in the integrated GTNEP are attributed to 5.5 MUSD (4.39%) from new transmission lines and 638.99 MUSD (2.61%) in the estimated energy cost of existing power plants. Conversely, there is an increased cost of 6.43 MUSD

(1.08%) in the estimated energy cost of new power plants and 3.05 MUSD (4.86%) in power losses.

It is concluded that considering the costs of existing generation units makes the benefits of integrated planning more noticeable. In scenario C2.1, the operating cost of existing generation units decreased compared to scenario C1.2. This reduction occurs because, in the projected system, the type C power plant has a lower energy generation cost than the existing power plants.

The results show that while each system presented unique challenges, the integrated GTNEP approach consistently outperformed the sequential planning method to achieve higher cost-effectiveness, regardless of the test system used. Therefore, the performance of the integrated GTNEP approach varies across these test systems primarily in terms of computational time and the number of objective function evaluations, as shown in Tables 5, 6, 7, 9, and 10. In summary, both computational time and objective function evaluations increase with the size of the test system, indicating greater computational complexity in larger systems, which can decrease the robustness of the method.

V. CONCLUSION

In this study, a methodology for the co-optimization of generation and AC transmission networks using meta-heuristic optimization techniques was proposed. The operational problem was formulated using mathematical representations of the AC power flow. The model considered incorporating new power plants, transmission lines, reactive power allocation, and the evaluation of network power losses. To the author's knowledge, this is the first work that has included these features in this problem. It was concluded that GEP and TNEP should be carried out in an integrated manner since this results in more economical expansion and operation plans, allowing for better resource management.

Results show that the type C power plant OCGT has the lowest levelized cost of energy compared to the non-conventional power plants used in this research, such as type A (coal-lignite) and type B CCGT units. This factor led to the inclusion of this generation unit in scenarios A2 and B2. By taking advantage of the lower operating costs and environmental benefits of renewable energy, scenario A3 highlights the importance of moving towards a more diverse and sustainable energy mix.

In the comparative analysis of meta-heuristics applied to the master problem of integrated generation and transmission network expansion planning, the efficiency of the hybrid meta-heuristic HBA-TS stands out. HBA-TS has proven to be more efficient, showcasing fewer objective function evaluations and, consequently, shorter computational times for simulations. This emphasizes the significance of HBA-TS as a valuable tool that can be applied to a wide range of other optimization processes, providing reassurance about the effectiveness of the optimization process.

While integrated planning offers superior economic benefits compared to sequential planning, it is essential to recognize that it requires higher computational time and increased objective function evaluations. The integrated approach involves a more detailed analysis, leading to longer processing times than the sequential approach. However, the long-term economic and operational advantages outweigh these timing concerns, particularly when considering the enhanced concurrent optimization of generation and transmission expansion planning.

Future research aims to incorporate contingencies and uncertainties into the planning process, implement dynamic planning strategies, and integrate emerging technologies such as HVDC links and storage devices. By addressing these aspects in future works, we can enhance the robustness and effectiveness of the planning framework, thereby ensuring the resilience and sustainability of power systems.

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