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Newly Developed Enhanced Imperialistic Competitive Algorithm for Design Optimization of an Autonomous Hybrid Green Power System

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Abstract: The importance of economics for owning hybrid green power systems (HGPS) warrants development of optimization methodologies with more effective search capabilities for determination of global minimum for costs. The objective of this study is to present several newly developed enhancements for imperialistic competitive algorithm (ICA) for design optimization of an autonomous HGPS with considerations for economics and reliability. HGPS examined consists of photovoltaic (PV) modules in a panel, wind turbines (WT), and storage batteries (SB). Utilizing an IEEE load profile and actual solar irradiation and wind speed data, the economics is evaluated based on annualized cost of system (ACS) and reliability constraint specified in terms of loss of power supply probability (LPSP). The simulation results show that enhanced ICA (EICA) developed in this study has a better convergence rate, as compared with other population based optimization methods such as ICA and genetic algorithm (GA). It is found that the new enhancements developed for EICA result in lower computation time for determining the optimal configuration of HGPS equipment by 40 and 79 % for ICA and GA, respectively. For LPSP of 2 %, it is determined that EICA results in lower ACS by 11.60 and 6 % in comparison with ICA and GA, respectively. For computation time, convergence occurs in 33, 55, and 160 minutes for EICA, ICA, and GA algorithms, respectively.

Keywords: Hybrid green power system, imperialistic competitive algorithm, design optimization, economics

1 Introduction

Green power technologies such as solar photovoltaic (PV) and wind turbine (WT) systems are considered as the most efficient and cost effective solutions for sustainable energy development due to their zero environmental emission during operation and decreasing manufacturing costs [1, 2].

For green power generation, it is determined that stand-alone solar or a wind energy system cannot provide a continuous electrical energy due to stochastic performance and weather variations [3], therefore, the independent use of these systems necessitates considerable redundancy for reliability purposes. For better reliability, it is possible to benefit from both solar and wind energy systems in a hybrid form, when the local climate conditions have enough potential in the level of solar irradiation and wind speed. Hybrid green power systems (HGPS) usually include PV panels and WTs to compensate for autonomy deficiencies. Also, proper storage devices are indispensable in supplying oscillatory load, when the HGPS generation is lower than load [4]. The load profile is extremely important in HGPS design optimization, as the requirement of lower loss of power supply probability (LPSP), implying lower outage probability, results in increasing capital costs. HGPS design optimization can lead to reduction in energy storage requirements, which could be a major economic restraint [5], and lessens the capital cost, while the consumer power supply continuity under varying atmospheric conditions is satisfied with acceptable level of reliability.

Clearly, the complexities in analysis of HGPS design necessitate employment of an appropriate design optimization method [6]. The number of modules in a PV panel and WTs, energy storage battery (SB) capacity and related peripheral equipment must be configured

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optimally, so that HGPS can provide a reliable service and operate unattended over its useful life span [3, 7]. Also, for design optimization of autonomous HGPS, data for solar irradiation, wind speed, and load profile to be met are necessary [8]. As noted by [9], for annual power support design, the region annual data bank and not any other periodic data should be used. To realize the full potential from utilization of green power systems, it is necessary to optimize the economics of owning and operating these systems. However, the mathematical relations governing the performance of green power systems, required for technical and economic analyses, are multi-variable and non-linear. Therefore, it is necessary to consider meta-heuristic methodologies, as alternatives to conventional mathematical approaches.

Meta-heuristic methodologies have been proven to be effective for optimization; however, the determination of global minimum always remains questionable due to inherent limitations in search capabilities of such methodologies [10, 11]. The ability of meta-heuristic optimization methods to find optimal solution for different applications has been examined in several studies. In general, meta-heuristic optimization methods have been developed utilizing population and individual based algorithms. Individual based methods such as simulated annealing [12] and tabu search [13] are fast enough for real-time applications but may be incapable for finding global minimum [14]. Population based methods such as genetic algorithm (GA) [15–17], particle swarm optimization algorithm [18–20], and imperialistic competitive algorithm (ICA) [21–27], have the ability of escaping from local minima at additional computation costs and, therefore, such algorithms are usually non-applicable to real-time problems [14] and, they are suitable for design optimization of systems, such as HGPS, where the optimal configuration of equipment is required for economic analyses.

While ICA has not been applied for design optimization of HGPS in the literature, the objective of this study is to present several newly developed enhancements for ICA for design optimization of an autonomous HGPS with considerations for economics and reliability. It is anticipated that ICA convergence rate could be improved via several enhancements based on extra heuristic mathematical operations for more effective skipping from local minima and reduced premature termination caused by high rate of convergence. Actual solar irradiation and wind speed data for Ardebil province of Iran are used in conjunction with IEEE reliability test system (RTS) load profile. Subject to LPSP as reliability constraint, annualized cost of HGPS system (ACS) is minimized as a function of five sizing variables considered in design optimization of this study, including the number of modules in PV panel, number of WTs, number of SBs, PV panel tilt angle, and WTs height.

The remaining of this study is organized as follows. Problem formulation is discussed in section 2. Section 3 provides description for optimization procedure based on ICA and EICA. Parametric values are given in section 4 and, then, results and discussion are presented in section 5. Finally, section 6 explains the conclusions and recommendations for future work.

2 Problem formulation

HGPS design optimization requires individual components modeling outlined in this section. As shown in Figure 1, a PV panel and WTs are used simultaneously to supply load. When there is sufficient power produced and hourly load is satisfied, surplus power is used to charge SB. In case of insufficient power to supply load due to lower solar irradiation or wind speed, SB begins to discharge. When maximum SB capacity is reached during charge mode, the excess energy is lost through dump load. To extract the maximum available power from the PV panel and WTs, maximum power point trackers (MPPT) are used. The chopper, as regulator, sets the common DC bus output voltage in its nominal band. The power produced by PV panel or WTs is transferred to DC bus where the DC/AC converter is used for connection to load.

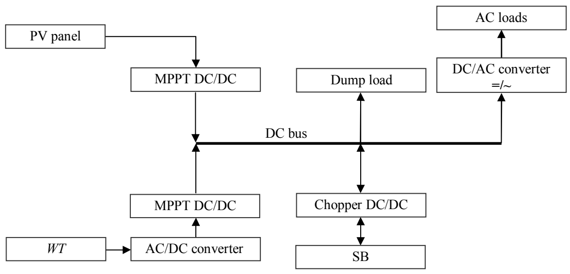

Fig. 1: Autonomous HGPS schematic diagram.

2.1 Photovoltaic power

The performance of a crystalline silicon PV module is a function of the physical variables of material, temperature, and solar irradiation. The maximum power output delivered by each module contained in PV panel is given by [28, 29]

$$P_{module} = FF.V_{oc}.I_{sc} = \frac{\frac{V_{oc}}{n_{MPP}.\frac{K.T}{q}} - \ln\left(\frac{V_{oc}}{n_{MPP}.\frac{K.T}{q}} + .072\right)}{1+\frac{V_{oc}}{n_{MPP}.\frac{K.T}{q}}} .\left(1-\frac{R_s}{\frac{V_{oc}}{I_{sc}}}\right).I_{sc0}\left(\frac{G}{G_0}\right)^{\alpha} . \frac{V_{oc0}}{1+\beta\ln\left(\frac{G_0}{G}\right)}.\left(\frac{T_0}{T}\right)^{\gamma} \quad (1)$$

All variables or constants are defined in [30] and parametric values are discussed later. If an equivalent array of $N_h.N_v$ modules is considered for PV panel, aggregated output power is [30]

$$P_{PV} = N_h.N_v.P_{module}.\eta_{MPPT}.\eta_{oth} \tag{2}$$

where η_{oth} is the factor representing the other losses such as those caused by cable resistance and accumulative dust. For PV output power calculation, solar irradiation on tilted surface is calculated based on hourly data for solar irradiation on horizontal surface for the particular location. Also, PV module temperature is determined while wind speed effect is observed [30].

2.2 Wind turbine power

The output power of a WT can be described by [30]

$$P_{WT} = \begin{cases} 0 & v < v_{ci} \text{ or } v > v_{co} \\ P_r.\frac{v-v_{ci}}{v_r-v_{ci}} & v_{ci} \leq v \leq v_r \\ P_r & v_r \leq v < v_{co} \end{cases} \tag{3}$$

Based on wind speed at a reference height v_{re}, the velocity at a specific hub height v for the location is estimated based on

$$v = v_{re}.(\frac{H_{WT}}{H_{re}})^{\zeta} \tag{4}$$

2.3 Storage battery power

As noted earlier, SB power can compensate for fluctuations in solar irradiation and wind power to improve the continuity in supplying load. The stored energy in each SB unit must be more than E_{SB_min} and less than E_{SB_max} and, it should not exceed maximum rate of its delivery due to its chopper transferability limit.

It must be noted that when the power available from HGPS exceeds $N_{SB}.E_{SB\_max}$, surplus energy is lost via dump load, then, for the particular hour

$$P_{dump\_load} = P_{PV} + P_{WT} - \frac{P_{AC\_load}(t)}{\eta_{con}(t)} \tag{5}$$

It is assumed that at the beginning, SB is in fully charged and its output voltage is nominal.

2.4 Reliability

LPSP is defined as the probability that a power supply deficit results when HGPS is unable to supply load. From t_i time to t_f [30]

$$LPSP = \frac{\sum_{t_i}^{t_f} Time(P_{available}(t) < P_{load}(t))}{t_f - t_i} \tag{6}$$

where LPSP=0% implies the load is always supplied whereas an LPSP=100% means that the load is never supplied.

The power required to meet the load is expressed as

$$P_{load}(t) = \frac{P_{AC\_load}(t)}{\eta_{conv}(t)} + \varphi.P_{dump\_load}(t) \tag{7}$$

where φ is a status coefficient equal to one in case of excess power generation and zero otherwise.

The power supplied from HGPS can be expressed by

$$P_{available}(t) = P_{PV} + P_{WT} + \sigma.P_{SB} \tag{8}$$

where σ is either zero or one for SB charging or discharging, respectively.

2.5 Economics

The economic evaluation based on ACS is the best criterion for HGPS analysis [30]. ACS for HGPS includes the annualized capital cost C_{acap}, annualized replacement cost C_{arep} for SB bank, and annualized maintenance cost C_{amain}. The miscellaneous equipment includes controller, inverter and rectifier for WT with AC output.

3 Optimization

3.1 Overview of ICA

ICA has a remarkable capability for finding global optimal solutions for a wide range of applications with noticeable convergence rate characteristic [21, 22]. ICA was originally proposed in [23] to solve continuous problems which uses imperialism and imperialistic competition process as a source of inspiration. Unlike most optimization methods that mimic natural behavior, ICA follows socio-political pattern. Through convergence process, countries or so-called colonies assimilate toward their respective imperialist [23]. Solid-line blocks in Figure 2 shows the computation sequence required for implementing ICA. Note that dashed-line blocks represent the added steps for the enhanced ICA (EICA), as discussed later in this section.

3.1.1 Initialization

Initially, ICA population is categorized into two different groups namely imperialists and colonies considering ACS as fitness index. For HGPS with five variables, a country is defined as [25]

$$country = [N_{PV}, N_{WT}, N_{SB}, \beta', H_{WT}] \tag{9}$$

where the variables are representative of number of PV modules, number of WTs, number of SB units, PV panel

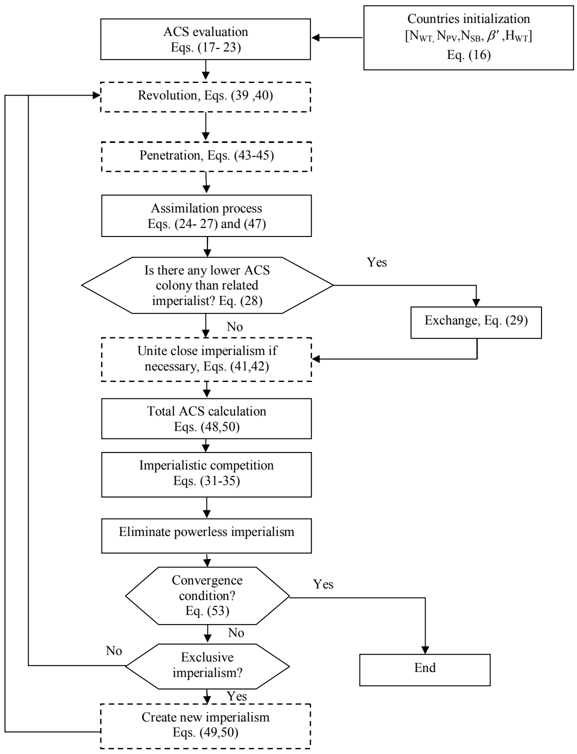

Fig. 2: Flowchart for ICA and EICA. The EICA enhancements introduced in this study are shown with dashed line blocks.

installation angle, and WTs height. respectively. The ACS for a country is given by

$$ACS(country) = ACS(N_{PV}, N_{WT}, N_{SB}, \beta', H_{WT}) \quad (10)$$

To start the optimization process, initial countries of size $N_{country}$ is produced. Then, based on lowest values for ACS, the most powerful countries as N_{imp} is selected out of $N_{country}$ to form the imperialists according to imperialistic fraction coefficient Λ. The remaining are considered as colonies where each colony belongs to one of imperialism, therefore

$$N_{imp} = \Lambda . N_{country} \quad (11)$$

$$N_{country} = N_{imp} + N_{col} \quad (12)$$

Next, the normalized ACS of nth imperialist is determined by

$$\overline{ACS}_{imp,n} = ACS_{imp,n} - max\{ACS_{imp,i}\} \quad (13)$$

where $ACS_{imp,n}$ is the ACS for the nth imperialist. Then, suitability of each imperialist is defined by

$$S_{imp,n} = \left| \frac{\overline{ACS}_{imp,n}}{\sum_{i=1}^{N_{imp}} \overline{ACS}_{imp,i}} \right| \quad (14)$$

Note that colonies are allocated to imperialists based on imperialists suitability indices. The initial number of colonies of the nth imperialism is

$$NC_{imp,n} = round\{S_{imp,n}.N_{col}\} \quad (15)$$

where N_{col} is the total number of initial colonies [25]. Utilizing aggregative operator on all NC_{imp}s results in

$$\sum_{i=1}^{N_{imp}} NC_{imp,i} = N_{col} \quad (16)$$

3.1.2 Assimilation

As in Figure 3, for two-dimensional optimization problem, a colony is attracted by its respective imperialist with respect to both axes. The direction of movement is based on the vector from the colony to the imperialist and l is a random variable with uniform distribution. Then

$$\text{Imperialist} = [\text{N}^*_{\text{PV}}, \text{N}^*_{\text{WT}}, \text{N}^*_{\text{SB}}, \beta'^*, \text{H}^*_{\text{WT}}] \quad (17)$$

$$d = | [N^*_{PV}, N^*_{WT}, N^*_{SB}, \beta'^*, H^*_{WT}] - [N_{PV}, N_{WT}, N_{SB}, \beta', H_{WT}] | \quad (18)$$

$$l \sim U(0, \lambda .d) \quad (19)$$

where assimilation coefficient $\lambda > 1$ causes the colonies to get closer to the imperialist position from both sides, which leads to better exploration around imperialist, and d is the distance between the colony and the imperialist. For widening the scope around the imperialist, a random deviation in directional angle θ is added to the direction of movement (Figure 3), where θ is a parameter with uniform distribution,

$$\theta \sim U(-\tau, \tau) \quad (20)$$

where τ adjusts the deviation from the original direction.

3.1.3 Position exchange

Through assimilation process, a colony may possess a position with better minimum and lower ACS than that of its imperialist,

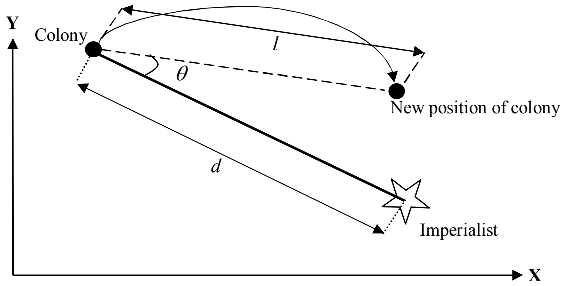

Fig. 3: Assimilation process ICA [24].

$$ACS(\overline{[N_{PV}, N_{WT}, N_{SB}, \beta', H_{WT}]}) < ACS([N^*_{PV}, N^*_{WT}, N^*_{SB}, \beta'^*, H^*_{WT}]) \quad (21)$$

As a result, an exchange between their positions occurs. In the next iteration, the previous imperialist turns up as a colony and related colonies change their trajectories toward the newly found imperialist,

$$Imperialist_{new\_position} = \overline{[N_{PV}, N_{WT}, N_{SB}, \beta', H_{WT}]} \quad (22)$$

3.1.4 Imperialism total power determination

The total power of imperialism is mainly affected by the power of an imperialist country. However, the power of the colonies of imperialism also has an effect given by

$$T\_ACS_{impm,n} = ACS_{imp,n} + \xi.mean\{ACS_{colonies\ of\ imperialism,n}\} \quad (23)$$

where $T\_ACS_{impm,n}$ is the total ACS of the nth imperialism and ξ is a positive small number as total ACS coefficient.

3.1.5 Imperialistic competition

During any iteration, the imperialists endeavor to possess colonies of other imperialists. At the beginning, the weakest colony that belongs to the weakest imperialism is selected based on its ACS and, then, the ownership probability of each imperialism is calculated according to the following approach. The possession likelihood related to any imperialism is commensurate with its total power. The normalized total ACS of nth imperialism is simply calculated by

$$\overline{T\_ACS}_{impm,n} = T\_ACS_{impm,n} - max\{T\_ACS_{impm,i}\} \quad (24)$$

Then, the ownership probability of any imperialism is given by

$$OP_n = \left| \frac{\overline{T\_ACS}_{impm,n}}{\sum_{i=1}^{N_{imp}} \overline{T\_ACS}_{impm,i}} \right| \quad (25)$$

The distribution of the segregated colony among imperialism is based on the following strategy. First, vector A is formed as

$$A = [OP_1, OP_2, OP_3, \cdots, OP_{N_{imp}}] \quad (26)$$

and then, vector Ra with the same dimension as A is generated in the way that its parameters originate from uniformly distributed random numbers,

$$Ra = [r_1, r_2, \cdots, r_{N_{imp}}], \quad r_1, r_2, \cdots, r_{N_{imp}} \in U(0,1) \quad (27)$$

and vector D is formed by subtracting Ra from A

$$D = A - Ra = [D_1, D_2, \cdots, D_{N_{imp}}] = [OP_1 - r_1, OP_2 - r_2, \cdots, OP_{N_imp} - r_{N_imp}] \quad (28)$$

According to vector D, the segregated colony is assigned to the imperialism whose relevant index in D is maximum.

Iteratively, ICA continues until predefined number of iterations is satisfied or convergence criteria are achieved.

It should be noted in ICA, the fitness for colonies and imperialist is evaluated based on ACS subject to a desired LPSP.

3.2 Proposed algorithm: EICA

The high convergence rate can lead ICA to get stuck in local minima, frequently, as it is discussed later. As shown by dashed-line blocks in Figure 2, the following enhancements increase EICA capability in finding global solution probability via more effective exploration of search space.

3.2.1 Fitness evaluation

For EICA, it is possible to evaluate the fitness for colonies and imperialists based on both ACS and LPSP, whereby, a more thorough examination of search space is achieved. EICA allocation policy, in its first generation, is defined based on primary allocation penalty coefficient ψ' in case of LPSP violation which performs as a weighting factor in

ACS^{EICA} calculation of each imperialist substituted in Eq. (20).

$$ACS^{\text{EICA}}_{imp,n} = \Big(\frac{ACS_{imp,n}}{\sum_{i=1}^{N_{imp}} ACS_{imp,i}}\Big) + \psi'\Big(\frac{LPSP_{imp,n}}{\sum_{i=1}^{N_{imp}} LSPS_{imp,i}}\Big) \quad (29)$$

The same process is adapted to total ACS^{EICA} calculation as total ACS^{EICA} penalty coefficient ψ through imperialistic competition substituted in Eq. (31).

$$T\_ACS^{\text{EICA}}_{impm,n} = ACS_{imp,n} + \xi \,.mean(ACS + \psi.LPSP)_{colonies\ of\ imperialism\_n} \quad (30)$$

Also, such an approach is considered for segregated colony specification in terms of imperialistic competition penalty coefficient ψ'',

$$ACS^{\text{EICA}}_{col,n} = ACS_{col,n} + \psi''.LPSP_{col,n} \quad (31)$$

3.2.2 Clustering

Through any iteration, EICA clusters all countries into two categories of closer and further ones according to the classification constant χ. Then, the revolution and penetration enhancements, as discussed later, are imposed on further and closer colonies, respectively. This approach serves as an equalizer between exploration and exploitation rate.

3.2.3 Revolution

Revolution is defined as a basic change in power or organizational structure that occurs in a relatively short period of time. Revolution causes a country to abruptly change its socio-political characteristics. Thus, during any iteration, in EICA, base on revolution coefficient of $\Re(\%)$, some colonies experience a stochastic change in their positions, which may not necessarily be toward their related imperialist. The revolution increases the exploration rate in EICA and prevents premature convergence of countries to local minima. In other words, revolution provides a condition in which some colonies are being authorized to have relative freedom in divergence to some extent. Note that a very high value of revolution coefficient can lead to convergence diminution to a great extent and, therefore, inferior final solutions could be anticipated. For example after a revolution, if the first and third variables are substituted, the country current position is revised as

$$country_{current\_position} = [N_{PV}, N_{WT}, N_{SB}, \beta', H_{WT}] \quad (32)$$

$$country_{current\_position} = [\overline{N}_{PV}, N_{WT}, \overline{N}_{SB}, \beta', H_{WT}] \quad (33)$$

3.2.4 Unification of similar imperialism

While all colonies and imperialists are moving toward the global minimum, some imperialists might reach close positions with respect to each other. When the number of design variables that have violated the predetermined threshold distance exceeds unification constant , the imperialists integrate to establish a new unified imperialism, which is a combination of both. All the colonies of two imperialists become the colonies of the new imperialism and the new imperialist is located in one of two imperialists positions. For instance, in case of two imperialists i and j

$$\varepsilon = [|\Delta N_{WT}|, |\Delta N_{PV}|, |\Delta N_{SB}|, |\Delta \beta'|, |\Delta H_{WT}|] \quad (34)$$

$$NC_{new\_imp} = NC_{imp\_i} + NC_{imp\_j} \quad (35)$$

3.2.5 Penetration

This enhancement is inspired from crossover strategy in GA which results in better convergence rate. Through assimilation process, because of high impression that exists between an imperialist and its countries, the penetration intensity coefficient $\kappa(\%)$ randomly allows for some variables to be substituted from imperialist array into a colony array.

$$country_{current\_position} = [N_{PV}, N_{WT}, N_{SB}, \beta', H_{WT}] \quad (36)$$

$$Imperialist = [N^*_{PV}, N^*_{WT}, N^*_{SB}, \beta'^*, H^*_{WT}] \quad (37)$$

$$country_{new\_position} = [N_{PV}, N^*_{WT}, N_{SB}, \beta', H^*_{WT}] \quad (38)$$

Through each EICA iteration, a random percentage of colonies according to the penetration coefficient κ' is chosen with the purpose of undergoing the penetration process.

3.2.6 Dynamic assimilation

The rate of colonies assimilating toward related imperialists changes through EICA optimization process. In other words, the assimilation coefficient λ is in dynamic mode and decreases gradually in line with EICA convergence through which the number of imperialists N_{imp} declines, progressively.

$$l \sim U(0, \lambda.(\frac{N_{imp}}{\Lambda.N_{country}}).d) \quad (39)$$

As a result, the search power increases around the imperialist, where the probability of global solution existence is more than any other location.

Furthermore, when there is optimization problem with more than three design variables, as it is in this study, the implementation of the random angle θ to a moving colony becomes difficult. The dynamic assimilation enhancement in EICA addresses this problem, where, for all colonies of the respective imperialist in imperialism, the parameter d array is multiplied by a random array, whereby a search in a more chaotic manner around each imperialist is achieved during the dynamic assimilation process,

$$colony_{new\_position} = [N^*_{PV}, N^*_{WT}, N^*_{SB}, \beta'^*, H^*_{WT}] + |d| - |l.rand(1,5)| \quad (40)$$

Note that any variable limit violation occurrence during assimilation process requires that the related variable is realigned to satisfy its admissible range.

3.2.7 Dynamic total ACS$^{\text{EICA}}$ coefficient

An enhancement to EICA is applied to ξ coefficient in Eq. (30) of ICA. In case of intense competition between two or more imperialists, which often occurs in situations where most imperialists have collapsed, the total power becomes more significant in determination of imperialism possessing the segregated colony than the power of imperialist alone, then

$$T\_ACS^{\text{EICA}}_{impm,n} = ACS^{\text{EICA}}_{imp,n} + \xi.(\frac{\Lambda.N_{country}}{N_{imp}}) .mean\{ACS^{\text{EICA}}_{colonies\ of\ imperialism,n}\} \quad (41)$$

3.2.8 New imperialist advent

Whenever the assimilation process leads to exclusive authority, the advent of new imperialists occurs periodically as an enhancement in EICA. This avoids premature occurrence of convergence and, as a result, the exploration scope increases. Some colonies allotted to the new imperialist grant it competition power against the last imperialism at least for limited number of iterations.

$$NC_{new\_imp} = \Upsilon.NC_{best\_imp} \quad (42)$$

where the advent coefficient Υ is an indicator for number of allocated colonies, and

$$NC_{best\_imp} = NC_{col} - NC_{new\_imp} \quad (43)$$

3.2.9 Dual mode coding

The proposed EICA simultaneously operates in both modes of discrete and continuous, as HGPS design variables include two continuous variables (β' and H), and three discrete variables (N_{PV}, N_{WT}, N_{SB}).

3.2.10 Weak imperialist augmentation

In ICA, weak imperialists lose their colonies rapidly. This characteristic may lead to disregard for some parts of search space which decreases global point finding probability. To surmount this problem, weak imperialist attraction probability is augmented to some extent both in primary allocation μ' and imperialistic competition μ coefficients. Consequently, it is anticipated to have more extensive search area for EICA and better solutions,

$$\overline{ACS}^{\text{EICA}}_{imp,n} = ACS^{\text{EICA}}_{imp,n} - \mu'.max\{ACS^{\text{EICA}}_{imp,i}\} \quad (44)$$

$$\overline{T\_ACS}^{\text{EICA}}_{impm,n} = T\_ACS^{\text{EICA}}_{impm,n} - \mu.max\{T\_ACS^{\text{EICA}}_{impm,i}\} \quad (45)$$

3.2.11 Termination criteria

As EICA eventually causes the countries to converge to the global minimum, different criteria can be used for termination. One way is to use predefined maximum iteration, referred to as maximum decades ε' used in this study. Also at the end, it is expected that only one imperialist with most impression and most authority continues to reign and all other imperialism collapse. As a consequence of this world order, all the parameters related to either the imperialism or the colonies are the same and the entire world is handled via a unique imperialist. Such ideality achievement can be defined as a termination for EICA, where best solution through different iterations does not improve for certain consecutive decades, or according to a threshold for a difference between mean ACS^{EICA} of whole imperialist and colony is reached,

$$|mean\{ACS_{imp}^{EICA}\} - mean\{ACS_{col}^{EICA}\}| < Threshold \quad (46)$$

3.2.12 EICA sensitivity analysis

The variation of different parameters values including constants and coefficients used in EICA are provided in Figure 4, where the chosen values are those that result in minimum value for ACS^{EICA} and they are listed in Table 1. It should be noted that during tuning process of each parameter, all other parameters are held fixed. EICA parameters tuning is according to a 53 sample-day period of year or one day a week.

Table 1: EICA parametric values resulting in optimum value for ACS

EICA parameters	Symbol	Value
Advent coefficient	Υ	0.20
Assimilation coefficient	λ	2.50
Classification constant	χ	1.06
Imperialistic competition coefficient	μ	0.80
Imperialistic competition penalty coefficient	Ψ''	5000
Imperialistic fraction coefficient	Λ	0.25
Penetration coefficient	κ'	1.00
Penetration intensity coefficient	κ	0.20
Primary allocation coefficient	μ'	0.60
Primary allocation penalty coefficient	Ψ'	4.00
Revolution coefficient	$\Re$	0.90
Total *ACS* coefficient	ξ	0.20
Total *ACS* penalty coefficient	Ψ	10000
Termination threshold	ε'	30
Unification constant	Φ	3
Unification threshold	ε	$[1,11,5,5^{\circ},4]$

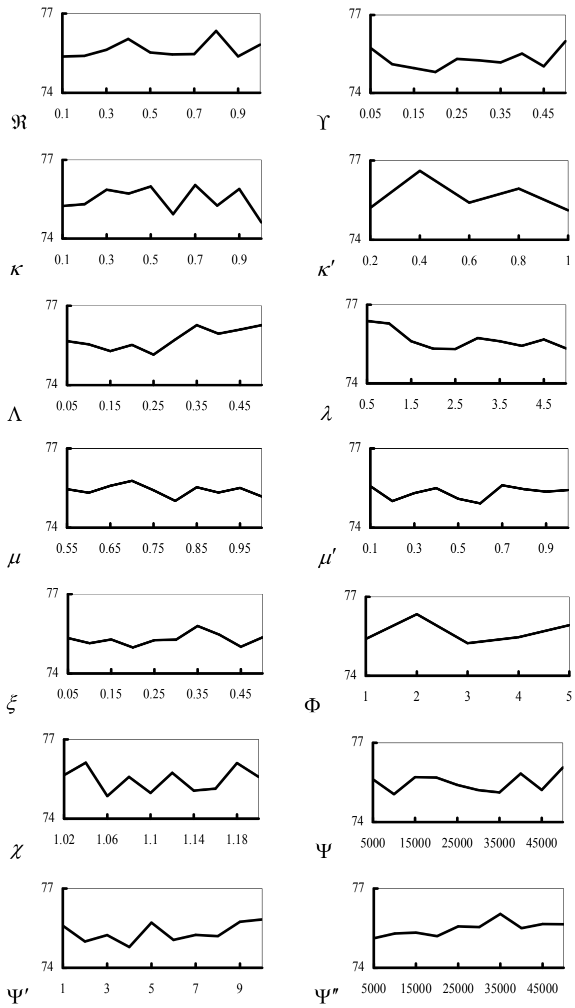

Fig. 4: Sensitivity analysis of EICA parameters including constants and coefficients: vertical axis represents the ACS ($\times 10^3$) (\$) and horizontal axis provides the range of values examined.

4 Parametric values

4.1 HGPS

Equipment characteristics used in this study are based on data for PV module, wind turbine, and SB given in Table 1, Figure 5, and Table 3. WTs height is set to be between $H_{min} = 10 \leq H \leq H_{max} = 50$ meters. For WTs, according to Figure 5, $v_{ci} = 2.5(m/s), v_{co} = 20(m/s), v_r = 12(m/s)$ and $P_r = 5kW$. For power law exponent, $\zeta \cong 0.14$ in Eq. (4), as it is considered for open land. Annual solar irradiation and wind speed hourly data input for HGPS design optimization is for Ardebil province in North-West of Iran, shown in Figure 6 (a) and (b). Hourly IEEE RTS load profile is considered as standard operational load depicted in Figure 6 (c). Costs and economic parameters for HGPS components are given in Table 4. For ACS calculations, interest and inflation rates are both equal to 6%. The ACS to be minimized for HGPS design optimization is expressed by [30]

$$MinACS = C_{acap}(N_{PV} + N_{WT} + N_{SB} + H + Mis) + C_{arep}(N_{SB}) + C_{amain}(N_{PV} + N_{WT} + N_{SB} + H + Mis) \quad (47)$$

Subject to

$$N_{PV}, N_{WT}, N_{SB} \geq 0 \quad (48)$$

$$H_{min} \leq H_{WT} \leq H_{max} \quad (49)$$

$$0 \le \beta' \le 90 \quad (50)$$

$$E_{SB\_min} \le E_{SB} \le E_{SB\_max} \quad (51)$$

$$|\Delta E_{SB}| \le |\Delta E_{SB\_max}| \quad (52)$$

$$LPSP_{cal} \le LPSP_{Desired} \quad (53)$$

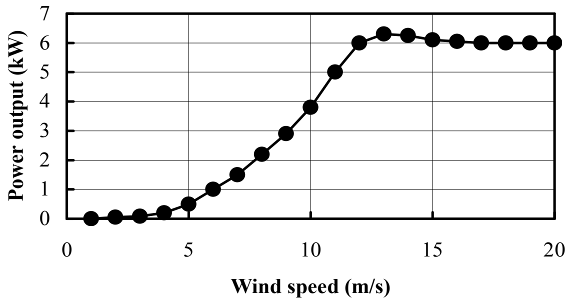

Fig. 5: Power output of WT as a function of wind speed [30].

Table 2: PV module characteristics for HGPS [30]

Type	V_{max} (V)	I_{sc} (A)	V_{max} (V)	I_{max} (A)	P_{max} (W)
Poly-crystalline silicon	21	6.5	17	5.73	100

Table 3: Specifications of a SB unit [31]

Rated capacity ($E_{SB\text{-}max}$) (kWh/unit)	Maximum conversion capacity (kWh/unit)	Minimum storage level ($E_{SB\text{-}min}$) (kWh/unit)	Useful life (year)	Efficiency (%)
8	3	3	10	85

Table 4: Costs and economic parameters for HGPS components [9, 30]

	Initial capital cost ($)	Replacement cost ($)	Maintenance cost in first year ($)	Lifetime (year)
PV module	6,500	-	65	25
WT	3,500	-	95	25
SB	800	700	10	10
Tower ($/m)	250	-	6.5	25
Miscellaneous components	8,000	-	80	25

In Eq. (2), although η_{MPPT} is a variable according to different working conditions, a constant value of $\eta_{MPPT} = 95\%$ is assumed for simplifying the calculations

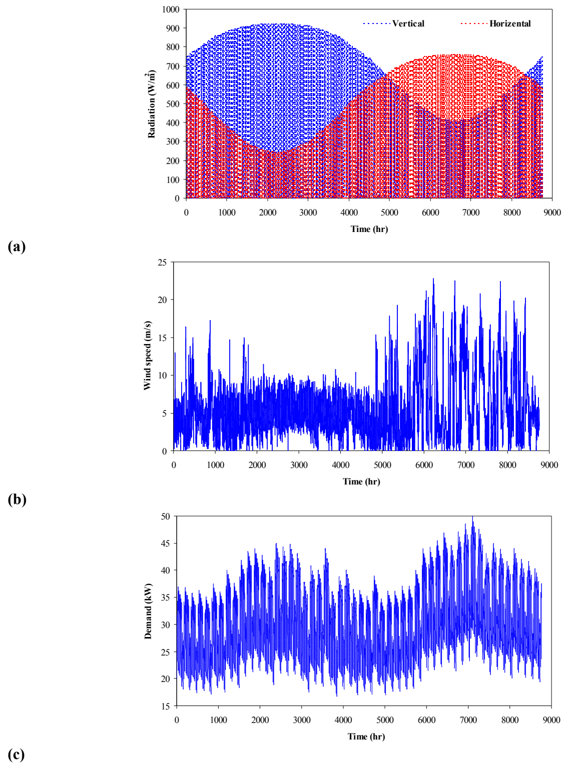

Fig. 6: (a) Hourly vertical and horizontal solar irradiation during a year, (b) Hourly wind speed during a year (at a height of 15 m), (c) Hourly IEEE RTS load profile [9].

and, $\eta_{oth} = 1$ [30]. The HGPS is studied based on using an hourly time step ($\Delta t = 1hr$) for one year. Converters operate at $\eta_{con}(t) = 1$ for both AC load or power resources.

4.2 EICA

To initialize EICA, 60 primary countries are generated randomly ($N_{country} = 60$) and $\Lambda = 25\%$ of countries are selected as imperialists $N_{imp} = 15$. Maximum iteration is $\varepsilon' = 30$ and it is used as termination criterion. The values of assimilation coefficient λ and τ are arbitrary but in most studies are about 2 and $\Pi/4$, respectively, which result in satisfactory convergence of countries to the global minimum [23], but according to sensitivity analysis $\lambda = 2.5$ leads to better solutions. Based on sensitivity analysis results (Figure 4), penetration and revolution coefficients values that minimize ACS^{EICA} are $\Re = 0.9$ and $\kappa' = 1$, respectively. New imperialist advent is in action after any imperialist collapses, immediately and, the number of colonies assigned to it is $\Upsilon = 0.2$ of the dominant imperialist colonies. While unification constant is $\Phi = 3$, thresholds for activating unification are considered as

$$\varepsilon = [1, 11, 5, 5^{\circ}, 4] \quad (54)$$

All other EICA parametric values resulting in optimum values for ACS^{EICA} are provided in Table 1.

5 Results and discussion

The proposed EICA, as a population based optimization method, is used and its performance is compared with those of ICA and GA for design optimization of HGPS. In this simulation study, the optimal configuration of equipment is determined, while ACS^{EICA} is minimized and reliability constraint is met. The design variables include the number of modules in the PV panel, number of WTs, number of SBs, PV panels slope angle, and WTs installation height.

During application of EICA, LPSP is calculated according to Eq. (6) and ACS for HGPS is estimated via Eq. (9). Then, there are two indices determined for each country, where EICA is used to determine the competency of each.

Simulation results for design optimization of HGPS based on ACS for LPSP=2% is shown in Table 5, where the optimal configuration of equipment is given for EICA, ICA, and GA.

Table 5: Optimal sizes of HGPS equipment determined using different algorithms

Parameter	*Optimization method*	*$LPSP_{Desired}$ 2 (%)*	*Change with respect to EICA (%)*
N_{WT}	EICA	6	-
	ICA	13	-54
	GA	5	+20
N_{PV}	EICA	903	-
	ICA	647	+40
	GA	1048	-13.8
N_{SB}	EICA	125	-
	ICA	167	-25
	GA	131	-4.6
H (m)	EICA	34	-
	ICA	28	+17.6
	GA	33	+3
β' (°)	EICA	46	-
	ICA	77	-40
	GA	53	-13.2
ACS ($\times 10^3$) ($)	EICA	93.406	-
	ICA	105.72	-11.6
	GA	99.38	-6
$LPSP_{cal}$ (%)	EICA	1.99	-
	ICA	1.99	0.0
	GA	1.38	+44.2

The convergence of all examined algorithms to find minimum values for ACS are shown in Figure 7, where it is observed that convergence time for EICA, ICA, and GA are 33, 55, and 160 minutes, respectively. It is observed that the problem with ICA getting trapped in a local minimum has occurred during 30 iterations in Figure 7. As in Figure 8 for variation of ACS as a function of LPSP after 10 iterations, EICA achieves the lowest ACS values for all LPSP values ranging from 1 to 10%.

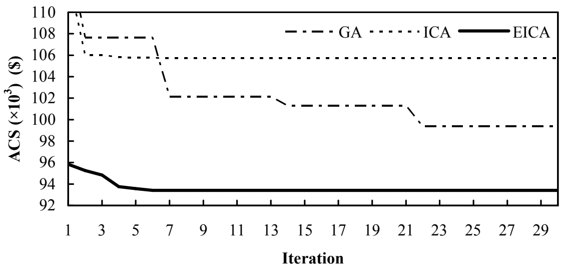

Fig. 7: Convergence for examined optimization algorithms.

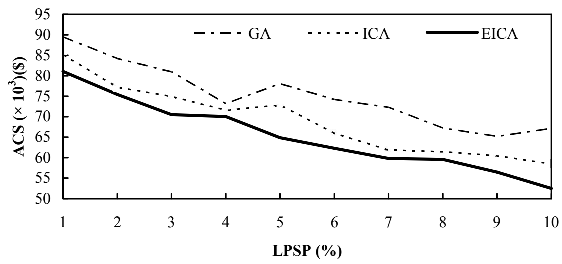

Fig. 8: Variation of ACS and LPSP for examined optimization algorithm.

It is determined that EICA results in lower ACS by 11.60 and 6% as compared with ICA and GA, respectively, for LPSP=2%. The annual cumulative dump load losses for EICA, ICA and GA final configuration are determined as 63, 116, and, 63 MWh, respectively.

A major advantage of EICA compared with other optimization algorithms, is fewer referrals to fitness function during consecutive iterations due to its high rate of convergence which is a time and memory-storage-consuming process, as it is 892, 1734, and 3120 for EICA, ICA and GA, respectively. This characteristic, particularly in industrial applications with a large number of variables, reduces the required computation time.

6 Conclusions and recommendations

In this study, several enhancements for ICA are developed and EICA is applied for design optimization of HGPS. The new enhancements of EICA include revolution, penetration, unification, and new imperialist advent in addition to dynamic design of parameters. It is concluded that EICA has a better performance in exploration of the search space and convergence rate leading to optimal configuration of HGPS equipment with the lowest ACS and comparable annual cumulative dump load losses, as compared with ICA and GA. Also, in comparison with ICA and GA, EICA requires the lowest convergence time. For future works, it is proposed to investigate the ability of EICA for minimization of environmental emissions for non-autonomous HGPS.

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