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Hybrid Bio-Inspired Computational Heuristic Paradigm for Integrated Load Dispatch Problems Involving Stochastic Wind

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Abstract: In this research work, bio-inspired computational heuristic algorithms (BCHAs) integrated with active-set algorithms (ASA) were designed to study integrated economics load dispatch problems with valve point effects involving stochastic wind power. These BCHAs are developed through variants of genetic algorithms based on a different set of routines for reproduction operators in order to make exploration and exploitation in the entire search space for finding the global optima, while the ASA is used for rapid local refinements of the results. The designed schemes are estimated on different load dispatch systems consisting of a combination of thermal generating units and wind power plants with and without valve point loading effects. The accuracy, convergence, robustness and complexity of the proposed schemes has been examined through comparative studies based on a sufficiently large number of independent trails and their statistical observations in terms of different performance indices.

Keywords: integrated power plants systems; economic load dispatch; active-set method; genetic algorithm; wind energy

1. Introduction

Economic load dispatch (ELD) is a fundamental issue in power plant systems, design and analysis with the aim of optimal scheduling of generated power in order to satisfy the load demand by least probable cost, while however, fulfilling the constraints on power generators [1–3]. Generally, the electricity generation cost with thermal power plants is excessively high and suitable planning is indeed needed to minimize the cost within reasonable levels. The ELD optimization problem is in one of the difficult constraints-based optimization systems in the power sector that usually needs excessive computations because of the nature of the cost functions and inherent non-smooth properties. A number of studies have introduced a variety of optimization procedures for ELD problems with and without valve point loading effect (VPLE) based on conventional and recently introduced meta-heuristics schemes, such as Newton methods [4,5], genetic algorithms [6], biogeography-based optimization algorithms [7], teaching learning based optimization methods [8], grey-wolf optimization algorithms [9], ant lion optimization procedures [10], modified krill herd algorithms [11,12], natural updated harmony searches [13], improved differential evolution [14], mine blast algorithms [15], and crow-search algorithms [16].

An additional aim in optimal load dispatch is to decrease or reduce the emissions that are dispersed due to the procedure of electricity generation. Normally, these environmental goals are conflicting with the economical nature of the systems, i.e., the decline in emission from generating units (GUs) results in the increased rate of electricity generation and vice versa. In such circumstances, multi-objective optimization techniques are exploited for combined ELD with emission problems, such as the symbiotic organisms search optimization method [17], simulated annealing algorithms [18], multi-objective evolutionary computing [19], multi-objective biogeography-based optimization [20], flower pollination algorithms [21], modulated particle swarm optimization [22] and chaotic bat algorithms [23].

The modern trend is to exploit the renewable energy assets for economical and unpolluted generation of electric power by incorporating the electricity generation scheme by use of wind power. The significant advantages of wind energy, besides the one-time initial cost of wind plants, are that there are no costs for production of power through wind, it is more environmentally friendly than thermal power plants and its ease in expendability i.e., installation of additional wind power generating units. There are some renewed applications of ELD involving wind energy, such as the binary artificial sheep method [24], integrated imperialist competitive with sequential quadratic programming [25], fuzzy adaptive artificial physics optimization [26], unit commitment problem involving wind power [27], multi-objective evolutionary algorithm [28] and group search optimizer with multiple producers [29]. All these existing procedures have their own competency, importance, applications and drawbacks in terms of precision, stability, and computing requirements. The research community has growing interest to design, explore and exploit modern stochastic solvers by using the strength of artificial intelligence procedures for applications in the diversified field of applied science and engineering, e.g., solution of stiff optimization problems arising in nanotechnology, nonlinear optics, astrophysics, atomic physics, plasma physics, electromagnetics, fluid mechanics, electric machines, piezoelectric systems, fractional order systems, bioinformatics, signal processing, controls, economic and finance [30–34] along with references therein. Additionally, there are many applications in which evolutionary computing paradigms are exploited through variants of genetic algorithms (GAs) based on different set of routines in the reproduction mechanism [35,36]. All of these are inspiring factors for authors to investigate in evolutionary stochastic paradigms for the solution of the emerging domain of energy and power sectors [37–40] including integrated power plant systems. As per our literature survey, evolutionary computing strategies based on variants of GAs have yet not been exploited in integrated power dispatch problems, therefore, the objective of the present study is to investigate integrated bio-inspired computational heuristic algorithms (BCHAs) based on the variants of GAs aid with the active-set algorithm (ASA) for optimization of load dispatch problems.

A brief summary of innovative contributions in terms of salient features of the proposed study are listed as:

- Novel applications of bio-inspired computational heuristic paradigms integrated with ASA is presented for accurate, stable, robust and efficient optimization of ELD, ELD with VPLE (ELD-VPLE), ELD-VPLE involving stochastic wind (ELD-VPLE-SW) problems.
- Global search strength of GAs and its variants is exploited for the design of BCHAs by using an appropriate set of routines for reproduction operators in order to make exploration of the entire search space supported with speedy local refinements with ASA.
- The performance of the designed schemes is estimated on ELD, ELD-VPLE and ELD-VPLE-SW problems based on a combination of thermal and wind power generating units by means of accuracy, convergence and complexity operators based on the results of statistics for a sufficiently large number of independent trails.
- The effective operation of BCHAs for integrated load dispatch scenarios, and other illustrative hallmarks for simplicity of the concept, coherent procedures with smooth implementation, robustness, expendability and stability.

The optimization procedure of BCHAs is described in Section 1; a brief overview of the system model of the integrated load dispatch system is presented in Section 2; the results with necessary interpretations are given in Section 3, while conclusions with future relevant studies are listed in Section 4.

2. Materials and Methods

2.1. System Model: Integrated Load Dispatch Problems

Three type of load dispatch problems are discussed in this study involving the no valve point loading effect (VPLE), with VPLE and VPLE involving stochastic wind power.

The fuel cost function for ELD with no VPLE: The total fuel cost of the power plant J_1 is modelled in this case with the help of the quadratic cost function and, it is given mathematically as:

$$J_1 = \sum_{i=1}^{N_g} \left[\left(a_i + b_i P_i + c_i P_i^2 \right) \right], \tag{1}$$

where N_g represents the total number of the power plants, a_i, b_i, as well as, c_i denote the fuel charge coefficients of ith power plant, and P_i gives the current output power of the ith plant.

The fuel cost function for ELD involving VPLE: The total fuel cost of the power plant J_1 is normally modelled with the help of the quadratic term based cost function, while the valve-point effect is similarly measured through adding of the sinusoidal term. The total fuel cost function is written as follows:

$$J_1 = \sum_{i=1}^{N_g} \left[\left(a_i + b_i P_i + c_i P_i^2 \right) + \left| e_{i..} \sin(f_i (P_{i.\min} - P_i)) \right| \right], \tag{2}$$

The coefficient e_i and f_i denote the fuel charge for the valve-point effect for the ith power plant.

The fuel cost function for ELD with VPLE and stochastic wind power: There are numerous ways that describe the importance of the functioning and forecasting cost in the scheme comprising of both thermal generators, as well as, wind turbines. Subsequently, the instant wind speed is arbitrary at some specified time, therefore, the operator might overestimate or underestimate the wind power availability. The cost function for the wind power generator is given mathematically as: [25]

$$J_2 = \sum_{j=1}^{m} \left[WPCost_{dir.j} + WPCost_{oe.j} + WPCost_{ue.j} \right], \tag{3}$$

where, $WPCost_{dir,j}$ represents the direct cost for the generation of wind power from the jth unit in MWh, $WPCost_{oe,j}$ denotes the overestimation cost for the jth wind generator in MWh and $WPCost_{ue,j}$ is defined for the underestimation of the cost of jth wind turbine in MWh.

The $WPCost_{dir,j}$ is directly related to the output wind power and it is given as:

$$WPCost_{dir} = \sum_{j=1}^{m} (q_j \times w_j) \tag{4}$$

where, q_j and w_j are the constant of direct electrical energy generation and real power generated by the jth wind generator in MWh, respectively.

Similarly, the $WPCost_{oe,j}$ can be presented as follows:

$$WPCost_{oe,j} = \sum_{j=1}^{m} (C_{rwj} \times E(Y_{oe,j})) \tag{5}$$

C_{rwj} denotes the charge constant for overestimation and underestimation of the jth wind generator in MW, while $E(Y_{oe,\,j})$ is the expected value of wind power overestimation and underestimation for the jth wind generator.

The $E(Y_{oe,j})$ is mathematically represented as follows: [25]

$$\begin{aligned} E(Y_{oe,j}) &= w_j\left[1-\exp\left(\frac{v_{in,j}^{Kj}}{C_j^{Kj}}\right)+\exp\left(-\frac{v_{out,j}^{Kj}}{C_J^{Kj}}\right)\right]+\left(\frac{w_{r,j}v_{in,j}}{v_{r,j}-v_{in,j}}+w_j\right)\left[\exp\left(-\frac{v_{in,j}^{Kj}}{C_j^{Kj}}\right)-\exp\left(-\frac{v_{1,j}^{Kj}}{C_j^{Kj}}\right)\right] \\ &+\left(\frac{w_{r,j}C_j}{v_{r,j}-v_{in,j}}\right)\left[\Gamma\left(1+\frac{1}{K_j}\left(\frac{v_{1,j}}{C_j}\right)^{Kj}\right)-\Gamma\left(1+\frac{1}{K_j}\left(\frac{v_{in,j}}{C_j}\right)^{Kj}\right)\right] \end{aligned}, \quad (6)$$

where, K_j and C_j are the shape and scale influence of Weibull distribution intended for the jth wind generator, respectively. The parameters, v_r, v_{in} and v_{out} stand for wind speed, cut in and cut out speeds in m/s, respectively. An intermediate constant v_1 is defined as $v_1 = v_{in} + (v_r - v_{in})w_1/w_r$. The wind turbine parameters w_j and w_r are representing the generated and rated power of the jth plant, respectively. Moreover, in (6), the symbol Γ with two parameters represent the incomplete gamma function as:

$$\Gamma(x,a) = \frac{1}{\Gamma(\mathrm{a})}\int_0^x t^{a-1}e^{-t}dt,$$

while, the symbol Γ with a single parameter represents the standard gamma function as:

$$\Gamma(x) = \int_0^x t^{x-1}e^{-t}dt$$

Similarly, $WPCost_{ue,j}$ can be presented as follows:

$$WPCost_{ue,j} = \sum_{j=1}^{m}(C_{pwj}\times E(Y_{ue,j})). \quad (7)$$

where, m denotes for number of wind generators, C_{pwj} defines the cost constant of underestimation for the jth wind generator in MWh and $E(Y_{ue,j})$ represents as the estimated charge of wind underestimation intended for the jth wind generator, while $E(Y_{ue,j})$ is provided mathematically as follows [25]:

$$\begin{aligned} E(Y_{ue,j}) = &\ (w_{r,j}-w_j)\left[\exp-\left(\frac{v_{r,j}^{Kj}}{C_j^{Kj}}\right)-\exp-\left(\frac{v_{out,j}^{Kj}}{C_j^{Kj}}\right)\right]+\left(\frac{w_{r,j}v_{in,j}}{v_{r,j}-v_{in,j}}+w_j\right)\left[\exp\left(-\frac{v_{r,j}^{Kj}}{C_j^{Kj}}\right)-\exp\left(-\frac{v_{1,j}^{Kj}}{C_j^{Kj}}\right)\right] \\ &+\left(\frac{w_{r.j}C_j}{v_{r,j}-v_{in,j}}\right)\left[\Gamma\left(1+\frac{1}{K_j}\left(\frac{v_{1,j}}{C_j}\right)^{Kj}\right)-\Gamma\left(1+\frac{1}{K_j}\left(\frac{v_{r,j}}{C_j}\right)^{Kj}\right)\right] \end{aligned} \quad (8)$$

Precisely, the cost function for integrated power plant systems is given as:

$$J = J_1 + J_2 \quad (9)$$

$$\begin{aligned} J = &\sum_{i=1}^{N_g}\left[\left(a_i+b_iP_i+c_iP_i^2\right)+\left|e_{i.}.\sin(f_i(P_{i.\min}-P_i))\right|\right] \\ &+\sum_{j=1}^{m}\left[WPCost_{dir.j}+WPCost_{oe.j}+WPCost_{ue.j}\right], \end{aligned} \quad (10)$$

where J_1 is given in Equation (2). Further necessary details of the system model for the interested readers can be seen in [25].

Constraints: The entire power generation based on thermal and wind generators should be equal to P_{load} line losses (P_{loss}) as follows:

$$\sum_{i=1}^{Ng}P_i + \sum_{j=1}^{m}w_j = P_{load} + P_{loss}, \quad (11)$$

where N_g represents the amount of power plants, m denotes the number of wind generators, P_i describesthe power of the ith power plant. w_j represents the generated power of the jth wind, P_{load} defines the total load demand and P_{loss} defines the line losses.

The losses of the transmission may be ignored for smaller transmission distance as well as for excessive load densities. However, in an enormous interrelated network wherever power is transferred above the extended distance through low load density regions, losses due to transmission are a foremost issue and distress the optimal dispatch. The mathematical relations of the losses are considered as follows:

$$P_{loss} = \sum_{I=1}^{Ng}\sum_{j=1}^{Ng} P_i B_{ij} P_j + \sum_{i=1}^{Ng} B_{i0} P_i + B_{00} \tag{12}$$

where, B_{ij}, B_{i0}, B_{00} is defined as the line loss coefficient and N_g represented the number of power plants. The active power of for each power plant, as well as, wind generators must fulfil the following bounds:

$$\begin{gathered} P_{i,\min} \leq P_1 \leq P_{i,\max} \\ 0 \leq w_j \leq w_{r,j} \end{gathered} \tag{13}$$

$P_{i,min}$ and $P_{i,max}$ are representing the maximum and minimum parameters of the ith power plant, respectively, while w_j and $w_{\mathrm{r,j}}$ denote the produced and rated power of the jth wind generator, respectively. Basically, the operational collection of the entire generators are restricted through their ramp rate confines. These limits are reflected as follows:

$$\begin{gathered} P_i^0 - P_i \leq D_i \\ P_i - P_i^0 \leq U_i \end{gathered} \tag{14}$$

P_i and $P_{\mathrm{i}}{}^0$ represent the current and prior output of the ith power plant, respectively, while D_i and U_i define the down and up ramp rate limits, respectively.

2.2. Optimization Techniques

The optimization procedure in this study consists of two parts. In the first part, the design of the bio-inspired heuristic algorithms based on the variant of GAs through its reproduction operators is presented, along with an overview of ASA used for rapid local convergence of the results. While in the second part, the learning procedure of these optimization algorithms to three constrained ELD systems involving VPLE and wind power generators is presented.

GAs is a meta-heuristic algorithm for viable global search and introduced by Holland in the 1970s [41]. GAs work through their fundamental operators of selection, crossover and mutation. These have been effectively utilized in diversified applications of constrained and unconstrained optimization problems with better control, stability, robustness and convergence. The workflow in terms of block structure for GAs is provided in Figure 1, while few potential applications of GAs in power sector can be seen in [42–44]. The steady state optimization performance of GAs is speeded-up by the process of combination with the efficient local search method based on ASA. ASA is one of the best local search procedures for linear and nonlinear, constrained and unconstrained optimization problems. The standard working of ASA is to divide the original stiff problems to relatively non-stiff sub-problems and these sub-problems are solved with the ease of algorithms. The block structure form of the workflow of ASA is shown in Figure 1. ASA addresses effectively many optimization problems which include nonnegative matrix factorization problems [45], variation deblurring problems [46] and warehouse location problems [47].

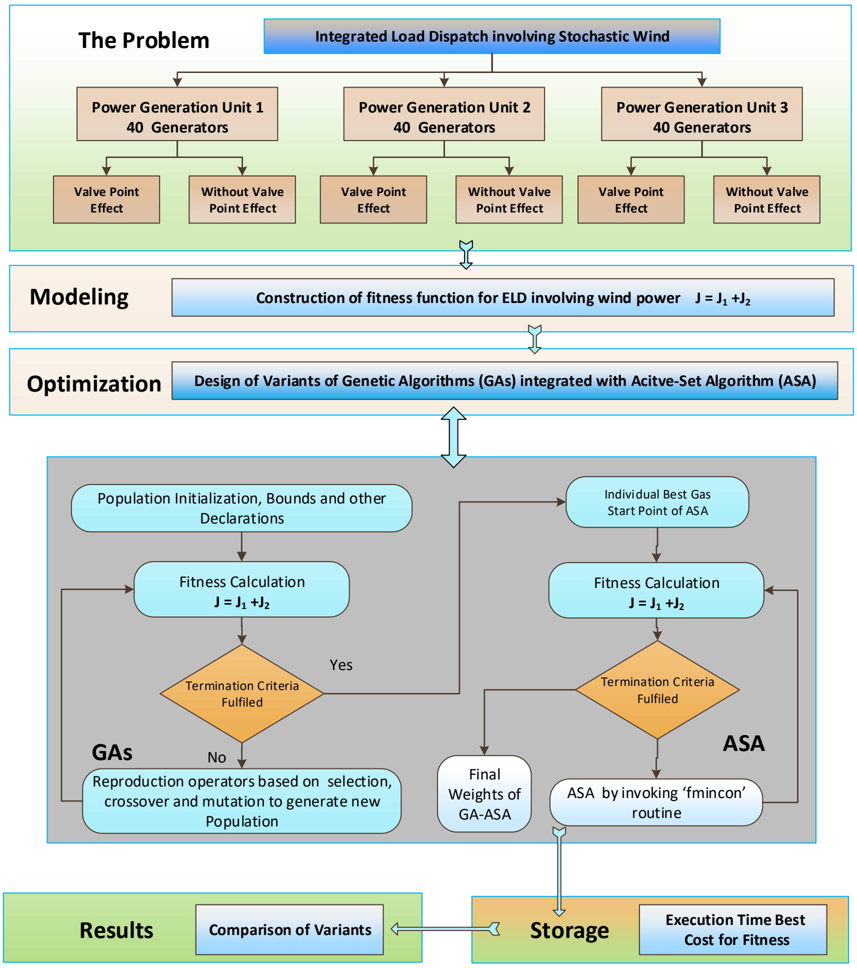


Figure 1. Graphical overview of the proposed design schemes for solving integrated economic load dispatch problems involving stochastic wind.

The paramount importance of GAs and ASA has encouraged the use of memetic variants of GAs with ASA (GA-ASA) for integrated load dispatch problems. Nine different sequential computing paradigms, GA-ASA-1 to GA-ASA-9 are designed for optimization based on a different set of reproduction operators as provided in Table 1. The selection operator stochastic uniform, means that GAs move along the line in steps of equal size. The section operator reminder, means that the probability for the selection of the parent is proportional to the fractional part of its scaled value. The selection operator roulette, means that an individual is chosen randomly with a probability equal to their respective area. The crossover operator heuristic, means an offspring that lies on the line containing their parents. The crossover operator arithmetic, means the create/generate offspring that are the weighted arithmetic mean of their parents. The crossover operator scatter, means a random one point, two point or intermediate crossover between the genes of two parents to have new child. The mutation operator adaptive feasible, means randomly generated feasible directions according to the last known successful or unsuccessful generation. The workflow diagram of the proposed approach is presented in Figure 1. In this study, implementation of variants of GAs and ASA is made through the optimization toolbox of the software package, Matlab with the help of ga, gaoptimset, fmincon and optimset routines. All three load dispatch problems are solved by these functions with appropriate settings of the parameters. The pseudocode of ASA is given in Algorithm 1.

Algorithm 1: Active-set Algorithm (ASA)

Inputs:

The best individual of nine variants of GAs for each ELD, ELD-VPLE and ELD-VPLE-SW in the case involving 40 generation units. Mathematically represented as:

$$P_{\mathrm{GA}} = \begin{cases} [P_1, P_2, \ldots, P_{40}] & \text{ELD} \\ [P_1, P_2, \ldots, P_{40}] & \text{ELD} - \text{VPLE} \\ [P_1, P_2, \ldots, P_{37}, \mathrm{W}_1, \mathrm{W}_2, \mathrm{W}_3] & \text{ELD} - \text{VPLE} - \text{SW} \end{cases},$$

Output: The refined weights by ASA represented as:

$$P_{\mathrm{GA}-ASM} = \begin{cases} [P_1, P_2, \ldots, P_{40}] & \text{ELD} \\ [P_1, P_2, \ldots, P_{40}] & \text{ELD} - \text{VPLE} \\ [P_1, P_2, \ldots, P_{37}, \mathrm{W}_1, \mathrm{W}_2, \mathrm{W}_3] & \text{ELD} - \text{VPLE} - \text{SW} \end{cases}$$

Initialization:

Initialize the values of random assignments, constraints and parameters of the ASA.

Termination:

Set stopping requirement of ASA as follows:

Maximum iterations/cycles i.e., 1000,

Tolerances

TolFun, i.e., 10^{-12},

TolCon, i.e., 10^{-12},

TolX) values, i.e., 10^{-10},

While {Stopping criteria achieved} **do**

Cost calculation:

Calculate the cost using Equations (1)–(3) for ELD, ELD-VPLE and ELD-VPLE-SW for 40 generating units

Stoppage

If any of termination is achieved, then exit from the loop, or else it continues.

Refinements

Refine the values of the decision variables at each iteration with ASA using the fmincong routine with algorithm active-set in the MATLAB optimization toolbox.

End

Storage

Store the values of decision variables for ELD, ELD-VPLE and ELD-VPLE-SW along with their costs, time, function count for current execution of ASA.

Statistics: Repeat the steps from initialization to storage for 100 trials for all nine variants of GA, i.e., GA-1 to GA-9 to generate a dataset of GA-ASA-1 to GA-ASA-9 results for comparative analysis of performance.

Table 1. The functions invoke to design the variants of the proposed optimization solvers based on genetic algorithms (GAs) supported with the active-set algorithm (ASA).

Methods	Invoke Routines of Reproduction Operators			Aided with
	Selection	Crossover	Mutations	'ASA'
GA-1	"Stochastic Uniform"	"Heuristic"	"Adaptive Feasible"	GA-ASA-1
GA-2	"Stochastic Uniform"	"Arithmetic"	"Adaptive Feasible"	GA-ASA-2
GA-3	"Stochastic Uniform"	"Scattered"	"Adaptive Feasible"	GA-ASA-3
GA-4	"Reminder"	"Heuristic"	"Adaptive Feasible"	GA-ASA-4
GA-5	"Reminder"	"Arithmetic"	"Adaptive Feasible"	GA-ASA-5
GA-6	"Reminder"	"Scattered"	"Adaptive Feasible"	GA-ASA-6
GA-7	"Roulette"	"Heuristic"	"Adaptive Feasible"	GA-ASA-7
GA-8	"Roulette"	"Arithmetic"	"Adaptive Feasible"	GA-ASA-8
GA-9	"Roulette"	"Scattered"	"Adaptive Feasible"	GA-ASA-9

3. Results and Discussion

The numerical experimentation of the all nine design schemes for three load dispatch problems based on 40 generation units (40-GUs) involving no VPLE, with VPLE and combined thermal, as well as, wind GUs with VPLE are presented in this section. The nine variants of GA were applied initially and later on, all the results of these variants were given to ASA for further refinements. The load demand (PD) remained fixed at 10,500 MW for all three load dispatch problems. The maximum generators output powers Pmax, the minimum generators output powers Pmin and the cost coefficients in the case of 40 GUs are given in Appendix A [48]. The parameter of wind GUs is given in Appendix B [25,49].

Cost function formulation: The cost function for ELD problems with 40 GUs, i.e., N_g = 40, having quadratic cost function using Equation (1), is written as:

$$J_1 = \sum_{i=1}^{40}\left[\left(a_i + b_iP_i + c_iP_i^2\right)\right] \tag{15}$$

where the values of Pmin, Pmax and cost coefficients vectors $\boldsymbol{a}$, $\boldsymbol{b}$ and $\boldsymbol{c}$ are given in Table A1 of Appendix A. The constraints associated with the problem are written as:

$$\mathrm{PD} = \sum_{i=1}^{40} P_i = 10500, \quad P_{i,\min} \le P_i \le P_{i,\max} \tag{16}$$

Similarly, the cost function for ELD problems with VPLE (ELD-VPLE) for 40 GUs, i.e., N_g = 40, is written as:

$$J = \sum_{i=1}^{40}\left[\left(a_i + b_iP_i + c_iP_i^2\right) + \left|e_{i\cdot}.\sin\left(f_i(P_{i.\min} - P_i)\right)\right|\right], \tag{17}$$

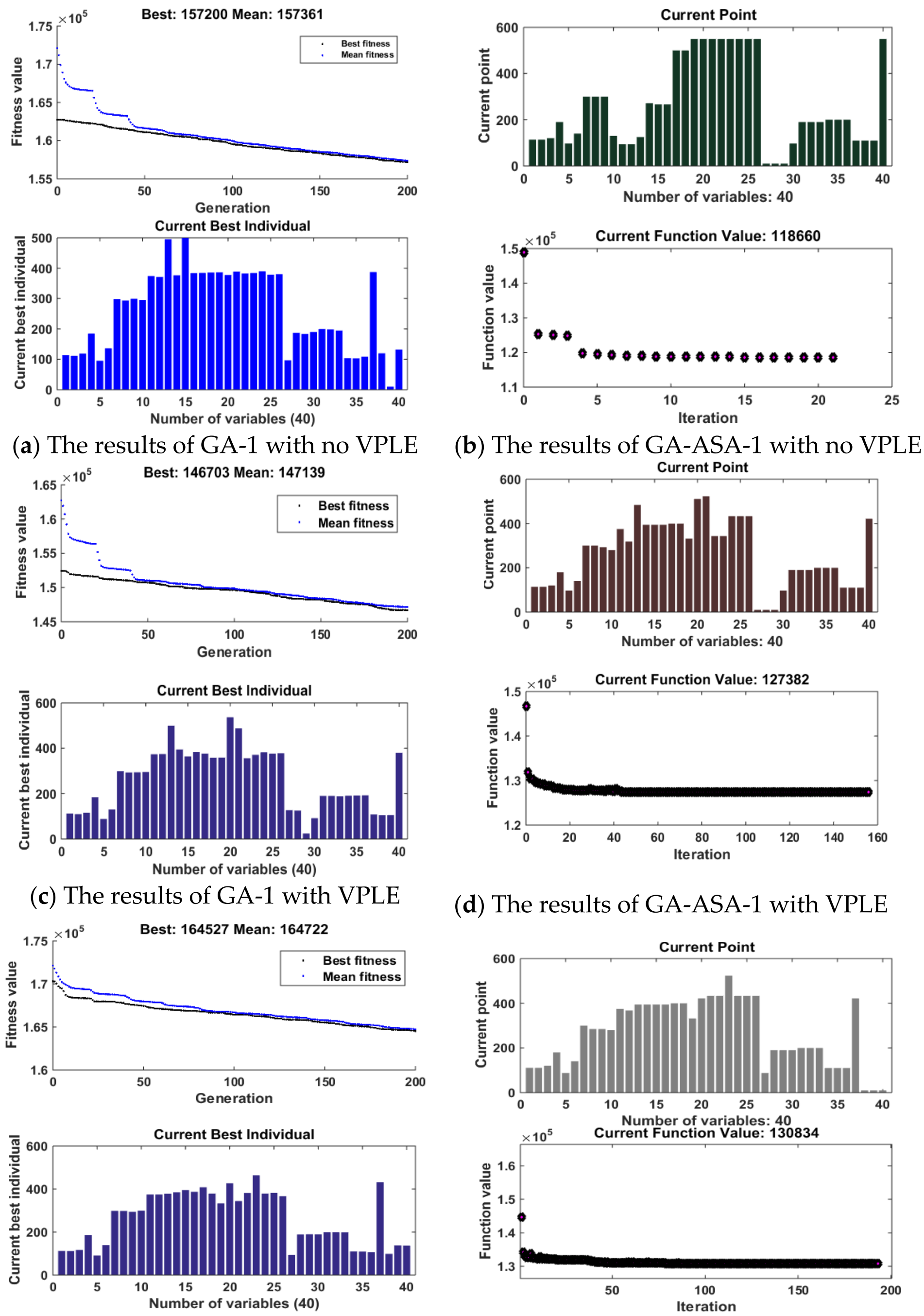
where the values of P_{min}, P_{max} along with cost coefficients vectors $\boldsymbol{a}$, $\boldsymbol{b}$, $\boldsymbol{c}$, $\boldsymbol{e}$ and $\boldsymbol{f}$ are given in Table A1 of Appendix A. The constraints associated with the problem are given in Equation (16).

The cost function for ELD problems involving VPLE by considering stochastic wind availability (ELD-VPLE-SW), in the case of 3 wind GUs, i.e., m = 3, and 37 thermal GUs, Ng = 37, are given as:

$$\begin{aligned} J = \; & \sum_{i=1}^{37}\left[\left(a_i + b_iP_i + c_iP_i^2\right) + \left|e_{i\cdot}.\sin\left(f_i(P_{i.\min} - P_i)\right)\right|\right] \\ & + \sum_{j=1}^{3}\left[WPCost_{dir.j} + WPCost_{oe.j} + WPCost_{ue.j}\right] \end{aligned} \tag{18}$$

where the values of P_{min}, P_{max} and cost coefficients vectors $\boldsymbol{a}$, $\boldsymbol{b}$, $\boldsymbol{c}$, $\boldsymbol{e}$ and $\boldsymbol{f}$ are given in Table A1 of Appendix A, while the parameter of wind generating units is given in Table A2 of Appendix B. The constraints associated with the problem are given in Equation (16).

The design nine variants of GA were applied to solve ELD, ELD-VPLE and ELD-VPLE-SW problems using the cost function given in Equations (15), (17) and (18), respectively, while satisfying the constraints given in Equation (16). The learning curves of GA-1 along its fitness value and output power are shown graphically in Figure 2a,c,e for ELD, ELD-VPLE and ELD-VPLE-SW problems, respectively. The global best weights of GA-1 for all three load dispatch problems are given to ASA for further refinements and respective results of GA-ASA-1 in Figure 2b,d,f. It can be seen that by the process of combination, a significant improvement in the values of the cost function was observed for all three load dispatch problems. Accordingly, the results of all nine variants of GA and GA-ASA were determined. The results of in terms of costs, time consumed, generation (Gen) executed, and fitness function evaluated (FE) are given in Table 2 for ELD, ELD-VPLE and ELD-VPLE-SW problems, while the results of output power Pi of GA and GA-ASA for all three load dispatch problems ELD, ELD-VPLE and ELD-VPLE-SW are listed in Tables A3–A5, respectively, of Appendix C. For ELD problems without considering VPLE, the minimum cost was achieved by GA-4 and the worst cost was achieved by GA-8, while no noticeable difference in time, generation (Gen) and function evaluated (FE) were observed (see data presented in Table 2). However, in the process of sequential computing the nine variants of GA-ASA, all nine algorithms converged to the same minimum cost. This is understandable given the ELD problems based on smooth/convex cost functions with unique local minima (see the results listed in Table 2).



(**a**) The results of GA-1 with no VPLE (**b**) The results of GA-ASA-1 with no VPLE

(**c**) The results of GA-1 with VPLE (**d**) The results of GA-ASA-1 with VPLE

(**e**) The results of GA-1 for VPLE-SW (**f**) The results of GA-ASA-1 for VPLE-SW

Figure 2. The adaptation of parameters of ELD systems based on 40 generating unit without considering VPLE, with considering VPLE and VPLE-SW.

Apart from the comparison of nine variants of GA and GA-ASA with each other, a detailed analysis of the proposed results in both cases of ELD-VPLE for 40GUs system and integrated power plant systems, i.e., ELD-VPLE-SW for 40GUs system with 3 wind units, is made with reported results. In the case of ELD-VPLE-SW, the results of reported solutions with Hybrid imperialist competitive-sequential quadratic programming (HIC-SQP) [25], PWTED1 [50], DWTED1 [50] and best compromise [50] are listed in Table 3. The best results were reported in HIC-SQP [25] for ELD-VPLE-SW based on the integrated load dispatch problem. Similarly, was the case for ELD-VPLE reported solutions for evolutionary programming aided with sequential quadratic programming (EP-SQP) [51], HIC-SQP [25], ant colony optimization (ACO) [52], biogeography-based optimization (BBO) [53], differential evolution aided with BBO (DE-BBO) [53], bacterial foraging optimization combined with Nelder–Mead (BF-NM) [54], new particle swarm optimization supported with local random searches (NPSO-LRS) [55] and real coded genetic algorithms (RCGA) [56]. The minimum cost achieved by HIC-SQP, PWTED1 and DWTED1 methods are listed in Table 3 for ELD-VPLE-SW, while the minimum costs of ES-SQP, HIC-SQP, ACO, BBO, DE-BBO, BF-NM, NPSO-LRS and RCGA for ELD-VPLE problems are also presented in Table 3. In the case of ELD-VPLE, the reported and our sequential computing algorithms have close resemblance with standard solutions, however none of the variants of GAs, GA-1 to GA-9 and their memetic computing techniques, i.e., GA-ASA-1 to GA-ASA-9, give the best solution reported so far for ELD-VPLE problems. Whereas, the significance of the proposed algorithms was evidently seen in the case of ELD-VPLE-SW problems based on the stiff cost function as defined in Equation (18), involving the calculation of incomplete gamma functions for each evaluation of the objective function. For example, the result achieved by the integrated computing approach GA-ASA-2 was 127,345.345$/h, which was better than the best reported optimization solutions for ELD-VPLE-SW problems in [25]. Additionally, it was observed that the proposed results of all nine variants of GA were poorer than in the reported results. However, after performance with ASA, the results of all nine variants of GA-ASA improved considerably, and even better than the reported results of recently applied algorithms based on HIC-SQP, PWTEDI, DWTEDI and best compromise.

Table 2. The results of GA and GA-ASA for ELD problems based on 40 GUs without considering VPLE, considering VPLE and integration of wind units.

Method	Without VPLE				With VPLE				VPLE and Stochastic Wind			
	Cost	Time	Gen	FCs	Cost	Time	Gen	FCs	Cost	Time	Gen	FCs
GA-1	132,514	90	200	30,150	137,359	97	200	30,150	147,325	115	200	30,150
GA-2	140,489	81	200	30,150	146,919	92	200	30,150	158,245	132	200	30,150
GA-3	138,246	98	200	30,150	146,458	90	200	30,150	157,408	95	200	30,150
GA-4	131,173	103	200	30,150	137,920	91	200	30,150	152,326	103	200	30,150
GA-5	140,158	85	200	30,150	146,664	96	200	30,150	158,229	117	200	30,150
GA-6	138,721	97	200	30,150	145,661	105	200	30,150	157,542	111	200	30,150
GA-7	133,351	88	200	30,150	139,825	101	200	30,150	148,987	101	200	30,150
GA-8	140,843	81	200	30,150	146,693	94	200	30,150	158,070	113	200	30,150
GA-9	139,700	100	200	30,150	145,944	88	200	30,150	157,778	99	200	30,150
GA-ASA-1	118,660	91	221	31,851	122,749	105	342	28,861	127,611	132	350	29,939
GA-ASA-2	118,660	82	224	32,094	122,719	100	324	27,325	127,744	143	237	20,288
GA-ASA-3	118,660	99	221	31,851	122,683	99	359	31,507	127,108	117	500	41,282
GA-ASA-4	118,660	104	223	32,013	122,369	98	276	22,760	127,510	112	202	16,912
GA-ASA-5	118,660	86	219	31,689	122,353	117	500	42,617	126,773	136	412	35,638
GA-ASA-6	118,660	98	222	31,932	122,175	101	229	19,182	127,141	121	198	16,411
GA-ASA-7	118,660	89	221	31,851	123,062	106	210	17,498	127,257	132	500	41,167
GA-ASA-8	118,660	82	221	31,852	122,796	104	343	29,568	127,038	122	204	16,916
GA-ASA-9	118,660	101	221	31,851	122,646	93	205	17,054	127,392	109	220	18,474

Table 3. The comparison of reported solutions in case of 40 thermal generating without VPLE and with VPLE.

Algorithm	ELD-VPLE	Algorithm	ELD-VPLE	Algorithm	ELD-VPLE-SW
EP–SQP	122,324.00$/h	BBO	121,688.6634$/hr	HIC-SQP	136,381.3831$/h
HIC-SQP	121,418.23$/hr	BF–NM	121,423.63$/hr	PWTEDI	137,985.38$/h
NPSO-RLS	123,094.98$/hr	DE–BBO	121,420.89$/hr	DWTEDI	137,190.31$/h
ACO	121,679.64$/hr	RCGA	121,628.59$/hr	Best compromise	143,587.90$/h

The analysis on multiple run of algorithms: The performance analysis on the basis of multiple runs for all nine variants of GA and GA-ASA were carried out to solve the optimization problems based on ELD, ELD-VPLE and ELD-VPLE-SW systems which consisted of 40 Gus, including both thermal and wind power plants.

The analysis on the precision and reliability were performed through a hundred independent trails of each variant of GA and GA-ASAs in order to optimize all three load dispatch problems. The results for GA-1 and GA-ASA-1 in terms of best cost against the number of runs of the algorithms for ELD, ELD-VPLE and ELD-VPLE-SW systems are shown in Figure 3a,b, respectively, while the histogram plots of GA-1 to solve the ELD, ELD-VPLE, and ELD-VPLE-SW are shown in Figure 3c–e, respectively, and respective histogram plots for GA-ASA-1 algorithms are plotted in Figure 3f–h. Accordingly, the best cost against number of runs along with their histogram studies were conducted for all three load dispatch problems for GA-2 and GA-3 as well as GA-ASA-2 and GA-ASA-3. Similarly, the results of the cost against the number of runs are shown in Figure 4 for GA-4 and GA-ASA-4, while in Figure 5 for GA-8 and GA-ASA-8. From Figure 3, a small variation in the values of GA-1 was observed for all the load dispatch models while such small oscillations were also evident in solving ELD-VPLE and ELD-VPLE-SW systems by GA-ASA-1. However, no variations were seen in ELD problems optimized with GA-ASA-1. The results in Figure 3 also showed that the same trend of GA-1 and GA-ASA-1 were followed by GA-2 to GA-3 and GA-ASA-2 to GA-ASA-3, respectively, for all three ELD, ELD-VPLE, ELD-VPLE-SW power generation systems. Accordingly, the similar behavior of the results is evidently seen from the rest of the illustrations presented in Figures 4 and 5.

The results presented in the histogram illustrations of Figure 3 showed that approximately 19%, 18% and 17% of the runs of GA-1 achieved costs ≤ 1.467×10^5, 1.515 1005 and 1.637×10^5 for ELD, ELD-VPLE, ELD-VPLE-SW power generation systems, respectively. However, 100%, 17% and 19% of the runs GA-ASA-1 obtained the cost ≤ 1.187×10^5, 1.254×10^5 and 1.301×10^5 for three respective load dispatch models. The results revealed that approximately 15%, 14% and 12% of the runs of GA-2 achieved the costs ≤ 1.526×10^5, 1.576×10^5 and 1.679×10^5 for ELD, ELD-VPLE, ELD-VPLE-SW power generation systems, respectively, while 100%, 15% and 14% of the runs GA-ASA-2 obtained the costs ≤ $1.187 \times 10^{5,}$ 1.252×10^5 and 1.297×10^5 for three respective load dispatch models. The results with similar observations were achieved by GA-3 to GA-9 as well as GA-ASA-3 to GA-ASA-9. Thus, it can be concluded that generally for non-smooth, as well as smooth cost functions of power dispatch problems, the memetic computing approaches, i.e., GA-ASA-1 to GA-ASA-9, provided relatively better results than the standalone approaches, i.e., GA-1 to GA-9.

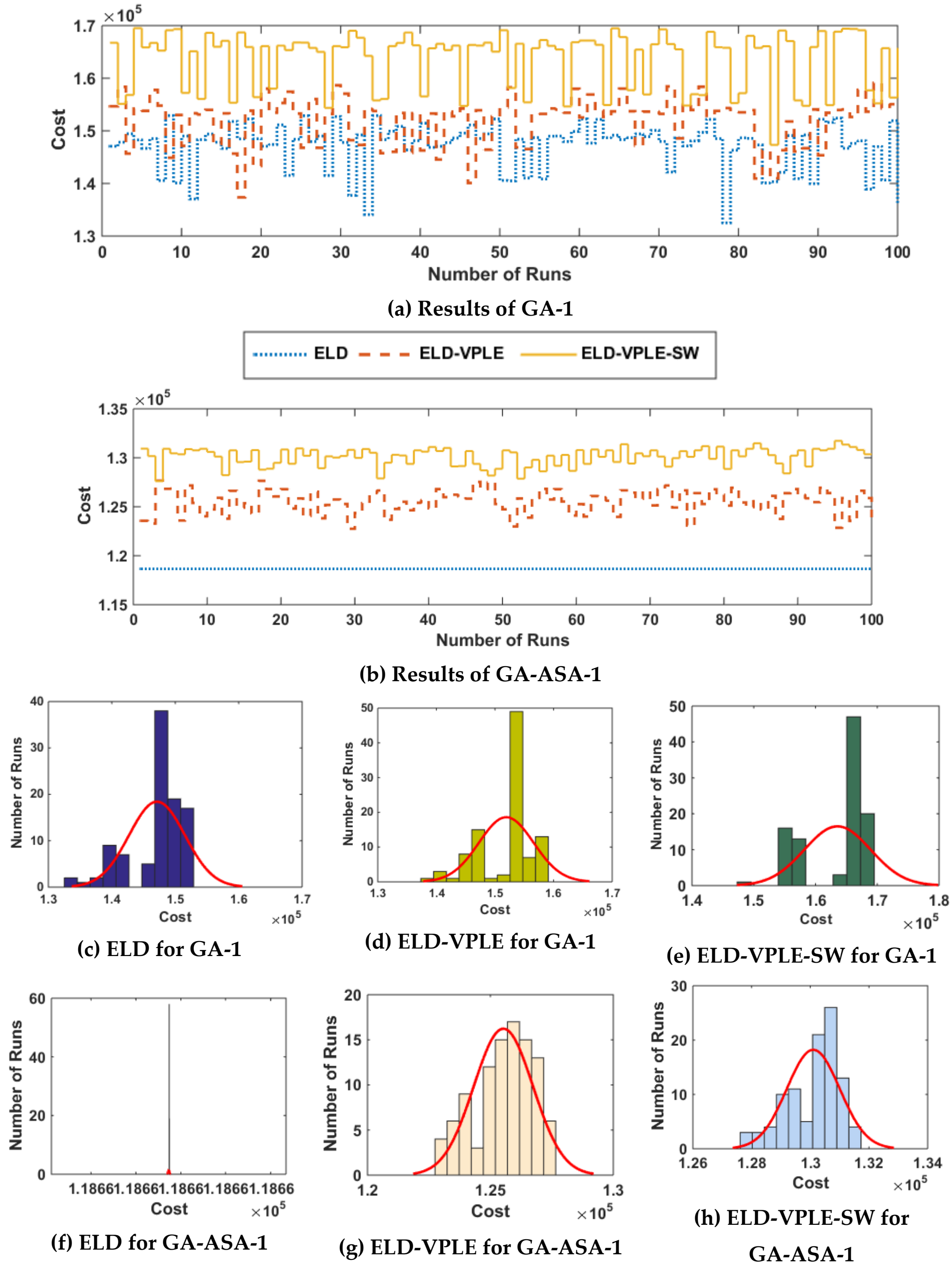
Complexity Analysis: The complexity analysis for all nine variants of GA and GA-ASAs are presented in terms of time consume, generation (Gen)/iteration executed and cost function evaluated /counted (FCs) for all three load dispatch systems. The result of complexity operators based on the mean along with its standard deviations (STD) magnitudes are presented in Table 4 for ELD, ELD-VPLE, ELD-VPLE-SW power generating systems in each case of GA and GA-ASAs. Regarding the ELD problem without VPLE, cost, time, Gen and FCs were 147,196 ± 4373, 92 ± 9, 174 ± 14 and 27,126 ± 6754 for GA, while for GA-ASA values of cost, time, Gen, FCs were 118,660 ± 0, 94 ± 12, 196 ± 7, and 28,036 ± 144. The cost, time, Gen and FCs were 152,000 ± 4000, 94 ± 10, 199 ± 20 and 29,000 ± 4000 for GA for ELD by considering VPLE, while for GA-ASA values of cost, time, Gen, FCs were 125,000 ± 1000, 95 ± 9, 428 ± 91 and 47,534 ± 7378. For ELD problems based on VPLE-SW, cost, time, Gen and FCs were 163,788.43 ± 4772.70, 98.37 ± 10.65, 173.60 ± 41.13 and 26,190.00 ± 222.00 for GA, while for GA-ASA the values of cost, time, Gen, FCs were 129,676.74 ± 897.77, 110.05 ± 11.23, 424.41 ± 83.55, and 47,214.99 ± 7472.99. The time based complexity analysis of the proposed variants GA-1 to GA-9, as well as, GA-ASA-1 to GA-ASA-9 is dependent on the specification of the machine on which optimization algorithms are executed. Thus, for better processing platforms, the computing time of optimization of the decision variable is reduced and vice versa. Similarly, varied computational requirement are associated with single generation/cycle of meta-heuristic paradigm based on GAs. Therefore, generations/iterations are also not effective for measurement of the complexity. To overcome these issues, the number of fitness function evaluated during the process of optimization of decision variables has been used as a measure for the analysis of the complexity which is a machine independent gauge. The complexity of the variants is given on the basis of time, iterations and FCs in the current study. These values are used for comparison whenever the same problems are addressed with counterpart meta-heuristic methodologies. The reported values of complexity in terms of time in seconds for the execution of a single generation/iteration were given 0.0597 for HIC-SQP [25] for ELD-VPLE-SW problems based on 37 thermal and three wind turbines based generated units. The CPU time per iteration of HIC-SQP [25] was better than reported PWTED1 [50], DWTED1 [50] and best compromise [50]. The similarly calculated values of complexity measure of proposed variants also provided the consumed time in close vicinity of the reported results.

Table 4. The comparison of results for ELD problems without considering VPLE, with considering VPLE and VPLE-SW through statistical performance indices.

Index	Method	Mean				STD			
		Cost	Time	Gen	FCs	Cost	Time	Gen	FCs
No VPLE	GA-1	147,125	92	200	30,150	4414	17	0	0
	GA-2	152,431	87	180	27,126	4739	8	43	6481
	GA-3	151,484	93	200	30,150	4897	13	0	0
	GA-4	145,951	96	200	30,150	4970	12	0	0
	GA-5	152,831	88	169	25,478	4482	12	52	7865
	GA-6	151,240	94	199	29,936	5034	11	14	2145
	GA-7	147,196	96	200	30,150	4261	9	0	0
	GA-8	152,119	91	174	26,309	4373	16	45	6754
	GA-9	150,732	91	199	30,050	4994	7	7	1005
	GA-ASA-1	118,660	92	221	31,880	0	17	2	126
	GA-ASA-2	118,660	88	202	28,905	0	8	43	6471
	GA-ASA-3	118,660	94	221	31,877	0	13	2	148
	GA-ASA-4	118,660	96	222	31,897	0	12	2	144
	GA-ASA-5	118,660	89	191	27,252	0	12	52	7861
	GA-ASA-6	118,660	95	220	31,676	0	11	14	2137
	GA-ASA-7	118,660	97	221	31,882	0	9	2	137
	GA-ASA-8	118,660	92	196	28,036	0	16	45	6758
	GA-ASA-9	118,660	92	221	31,799	0	7	7	1012
VPLE	GA-1	151,927	97	200	30,150	4662	11	0	0
	GA-2	157,187	90	183	27,611	4764	13	44	6567
	GA-3	156,530	90	199	29,960	5076	11	13	1905
	GA-4	153,248	97	200	30,150	4392	13	0	0
	GA-5	158,020	88	183	27,662	4735	8	41	6083
	GA-6	157,193	97	199	29,955	4814	12	13	1950
	GA-7	152,499	98	200	30,150	4590	10	0	0
	GA-8	158,255	93	185	27,929	4482	16	40	5975
	GA-9	157,775	94	200	30,150	4611	7	0	0
	GA-ASA-1	125,528	103	445	51,028	1206	11	76	6701
	GA-ASA-2	125,137	95	428	48,342	1194	13	90	9677
	GA-ASA-3	125,381	97	454	51,574	1196	12	97	8408
	GA-ASA-4	125,238	104	459	52,228	1223	13	95	8366
	GA-ASA-5	125,072	94	433	48,842	1218	9	83	8732
	GA-ASA-6	125,287	102	453	51,564	1236	12	91	8065
	GA-ASA-7	125,657	104	444	50,849	1060	10	74	6405
	GA-ASA-8	125,411	99	416	47,534	1146	16	85	8818
	GA-ASA-9	125,375	100	445	50,903	1171	7	88	7378
VPLE-SW	GA-1	163,557	108	200	30,150	5362	11	0	0.00
	GA-2	167,796	98	171	25,747	4834	12	51	7741
	GA-3	167,815	102	200	30,150	4580	9	0.00	0
	GA-4	163,848	108	200	30,150	4817	150	0	0
	GA-5	167,456	99	173	26,190	4772	11	46	6932
	GA-6	167,024	105	200	30,150	5090	16	0	0
	GA-7	163,788	108	200	30,150	4841	12	0	0
	GA-8	167,120	98	180	27,130	5146	10	41	6169
	GA-9	167,539	103	199	29,928	4738	9	14	2220
	GA-ASA-1	130,102	110	436	50,183	901	11	77	6565

Table 4. *Cont.*

Index	Method	Mean				STD			
		Cost	Time	Gen	FCs	Cost	Time	Gen	FCs
VPLE-SW	GA-ASA-2	129,706	109	424	47,214	975	13	101	10,589
	GA-ASA-3	129,828	114	448	51,198	955	10	89	7450
	GA-ASA-4	130,075	120	445	51,112	914	15	84	7472
	GA-ASA-5	129,824	110	414	46,775	1010	12	96	10,323
	GA-ASA-6	129,813	117	449	51,319	898	16	88	7699
	GA-ASA-7	130,248	119	440	50,683	849	13	83	7516
	GA-ASA-8	129,661	110	428	48,115	1030.	11	95	9821
	GA-ASA-9	129,677	115	456	51,859	895	11	92	8308



(a) Results of GA-1

(b) Results of GA-ASA-1

(c) ELD for GA-1

(d) ELD-VPLE for GA-1

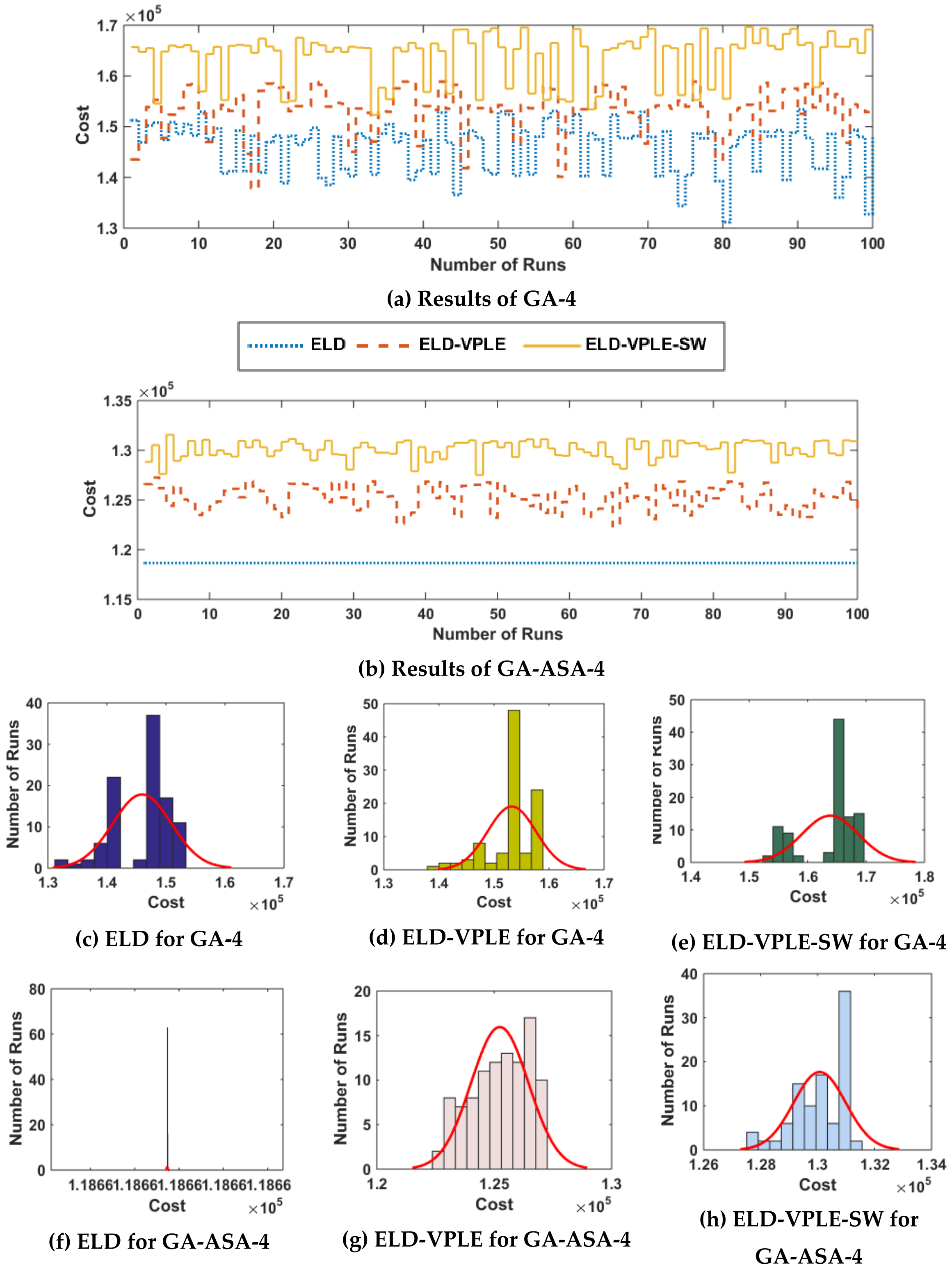
(e) ELD-VPLE-SW for GA-1

(f) ELD for GA-ASA-1

(g) ELD-VPLE for GA-ASA-1

(h) ELD-VPLE-SW for GA-ASA-1

Figure 3. The comparison of results on the basis of 100 independent runs of GA-1 and GA-ASA-1 for all three load dispatch problems.



(a) Results of GA-4

(b) Results of GA-ASA-4

(c) ELD for GA-4

(d) ELD-VPLE for GA-4

(e) ELD-VPLE-SW for GA-4

(f) ELD for GA-ASA-4

(g) ELD-VPLE for GA-ASA-4

(h) ELD-VPLE-SW for GA-ASA-4

Figure 4. The comparison of results on the basis of 100 independent runs of GA-4 and GA-ASA-4 for all three load dispatch problems.

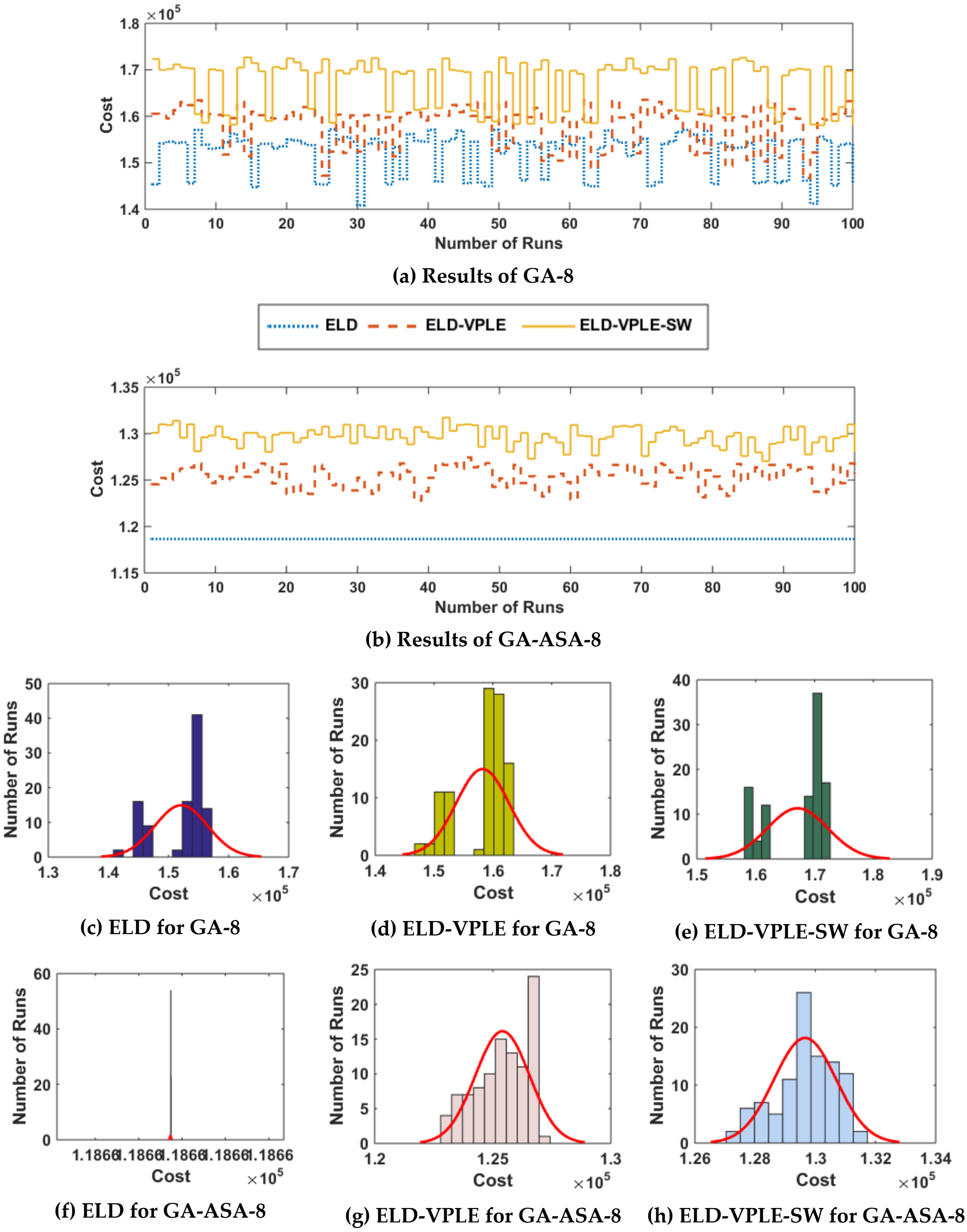


Figure 5. The comparison of results on the basis of 100 independent runs of GA-8 and GA-ASA-8 for all three load dispatch problems.

4. Conclusions

The conclusions are summarized as follows:

- Bio-inspired computational heuristics is exploited for solving effectively the integrated power plants systems based on thermal and wind generating units. The proposed BCHAs were based on nine variants of GAs and were designed by using different sets of reproduction operators and each global search method was aided with ASA for rapid local convergence.

- The performance of proposed schemes was examined for solving ELD, ELD-VPLE, ELD-VPLE-SW problems based on 40 generating units with a fix load demand of 10,500 MW. It was found that all nine integrated approaches were viable solvers with reasonable accuracy. Additionally, sequential computing schemes gave relatively better results than standalone approaches.
- Regarding the smooth cost function based ELD problem, there was no difference in the performance for each integrated methodology, while in the variants of Gas, the best cost was achieved using GA-4, i.e., 131,173.36$/hr, while in case of GA-ASA, the best minimum cost was achieved through GA-9, i.e., 118,600$/hr.
- Regarding the non-convex cost function based ELD-VPLE problem, the minimum cost was achieved using GA-ASA-1, i.e., 137,359$/hr., while the results of combined optimization approaches were relatively better than GA variants. However the best minimum cost was achieved by standalone GA-6 is 122,175$/hr.
- The scenario of the integrated power plant system was represented with ELD-VPLE-SW. The most effective optimization solver was GA-1 in terms of accuracy and convergence for the standalone scheme, while for sequential computing schemes, the results of GA-ASA-8 were found to be superior.
- The validation and verification for the performance of each optimization solver was established from 100 independent trails to solve all three load dispatch problems by using the detailed analysis through statistical operators, convergence curves, as well as, histogram illustrations.

Some potential research directions are briefly narrated as:

- The presented nine variant of GAs aided ASA, can be a good alternative to be explored or exploited in future for the unit commitment problem in the energy sector.
- The application of proposed optimization algorithms can be explored for a variety of integrated load dispatch problems based on wind, solar, hydel, and biomass, generating units for dynamic and static requirements.
- The newly introduced optimization solvers, including fractional order partial swarm optimization algorithms, fireworks algorithms, moth-flame algorithms, backtracking search optimization algorithms and differential search optimization algorithms can give quality solutions for problems arising in integrated power plant systems.

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Conflicts of Interest: The authors have no conflicts of interest to declare.

Appendix A

The parameters of thermal 40GUs based load dispatch systems are provided in Table A1.

Table A1. The parameters of 40GUs system based ELD problems.

Generator	Pmin (MW)	Pmax (MW)	*a*	*b*	*c*	*e*	*f*
1	36	114	0.00690	6.73	94.705	100	0.084
2	36	114	0.00690	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	47	97	0.0114	5.35	148.89	120	0.077
6	68	140	0.01142	8.05	222.33	100	0.084

Table A1. *Cont.*

Generator	Pmin (MW)	Pmax (MW)	*a*	*b*	*c*	*e*	*f*
7	110	300	0.00357	8.03	287.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.60	455.76	200	0.042
10	130	300	0.00605	12.9	722.82	200	0.042
11	94	375	0.00515	12.9	635.20	200	0.042
12	94	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	913.40	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00248	6.66	794.53	300	0.035
24	254	550	0.00248	6.66	794.53	300	0.035
25	254	550	0.00277	7.10	801.32	300	0.035
26	254	550	0.00277	7.10	801.32	300	0.035
27	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.01140	5.35	148.89	120	0.077
31	60	190	0.00160	6.43	222.92	150	0.063
32	60	190	0.00160	6.43	222.92	150	0.063
33	60	190	0.00160	6.43	222.92	150	0.063
34	90	200	0.0001	8.95	107.87	200	0.042
35	90	200	0.0001	8.62	116.58	200	0.042
36	90	200	0.0001	8.62	116.58	200	0.042
37	25	110	0.0161	5.88	307.45	80	0.098
38	25	110	0.0161	5.88	307.45	80	0.098
39	25	110	0.0161	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

Appendix B

The parameters of wind based generating units are provided in Table A2.

Table A2. The parameters of wind based generating units.

C_1	C_2	C_3	K_1	K_2	K_3	D_1	D_2	D_3
8	7	6	2	2.4	1.7	120	120	120
$V_{1(m/s)}$	$V_{in(m/s)}$	$V_{out(m/s)}$	$C_{rw1(MWh)}$	$C_{rw2(MWh)}$	$C_{rw3(MWh)}$	$C_{rp1(MWh)}$	$C_{rp2(MWh)}$	$C_{rp3(MWh)}$
14	4	25	30	30	30	30	30	30

Appendix C

The results in terms of power output of GA and GA-ASA for ELD, ELD-VPLE and ELD-VPLE-SW problems are provided in Tables A3–A5, respectively.

Table A3. The results in terms of power output of GA and GA-ASA for ELD problems based on 40 GUs without considering VPLE.

GU	Variants of GA									Variants of GA-ASA								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
P_1	104.26	110.42	109.93	108.01	110.53	109.02	113.23	110.54	110.81	114.00	114.00	114.00	114.00	114.00	114.00	114.00	114.00	114.00
P_2	113.01	110.42	110.03	102.85	110.23	110.64	106.01	110.66	110.87	114.00	114.00	114.00	114.00	114.00	114.00	114.00	114.00	114.00
P_3	114.99	116.41	115.98	104.70	116.29	114.98	114.29	116.15	115.69	120.00	120.00	120.00	120.00	120.00	120.00	120.00	120.00	120.00
P_4	182.22	186.42	186.97	172.97	186.67	185.92	179.14	186.66	186.25	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_5	89.13	94.42	93.97	87.16	93.39	94.72	93.05	93.66	93.41	97.00	97.00	97.00	97.00	97.00	97.00	97.00	97.00	97.00
P_6	135.77	136.42	135.95	133.55	136.23	134.90	134.15	137.15	136.72	140.00	140.00	140.00	140.00	140.00	140.00	140.00	140.00	140.00
P_7	294.78	296.42	295.95	299.36	296.24	296.90	294.66	296.17	294.29	300.00	300.00	300.00	300.00	300.00	300.00	300.00	300.00	300.00
P_8	291.76	296.42	296.02	283.74	296.45	296.86	297.37	296.66	294.97	300.00	300.00	300.00	300.00	300.00	300.00	300.00	300.00	300.00
P9	288.03	296.42	295.96	289.37	296.33	297.55	295.84	297.65	295.87	300.00	300.00	300.00	300.00	300.00	300.00	300.00	300.00	300.00
P_{10}	296.96	296.42	295.89	290.86	296.96	295.76	292.06	296.63	296.84	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00	130.00
P_{11}	373.38	371.42	371.85	356.12	371.22	370.86	374.90	371.64	370.71	94.00	94.00	94.00	94.00	94.00	94.00	94.00	94.00	94.00
P_{12}	370.31	371.34	370.99	349.42	371.08	370.25	370.45	371.66	370.55	94.00	94.00	94.00	94.00	94.00	94.00	94.00	94.00	94.00
P_{13}	378.98	379.80	380.47	370.85	414.06	379.75	491.18	378.19	379.83	125.00	125.00	125.00	125.00	125.00	125.00	125.00	125.00	125.00
P_{14}	394.11	377.49	379.90	376.44	382.13	385.65	376.03	380.76	380.08	271.67	271.67	271.67	271.67	271.67	271.67	271.67	271.67	271.67
P_{15}	379.10	378.53	378.85	452.45	414.08	392.10	380.98	377.65	381.58	266.66	266.66	266.66	266.66	266.66	266.66	266.66	266.66	266.66
P_{16}	499.11	378.31	378.30	372.42	380.44	381.36	367.90	381.11	377.84	266.66	266.66	266.66	266.66	266.66	266.66	266.66	266.66	266.66
P_{17}	294.15	379.64	379.34	395.28	418.37	380.64	376.86	377.86	379.01	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00
P_{18}	374.92	378.35	378.34	378.94	416.93	377.17	491.13	437.12	377.14	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00	500.00
P_{19}	381.67	445.45	380.76	429.41	427.37	444.50	316.51	380.84	449.02	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00
P_{20}	374.44	378.68	445.85	366.75	381.05	378.64	503.95	437.49	381.23	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00
P_{21}	367.83	515.23	379.20	349.20	380.51	380.31	380.01	379.08	446.48	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00
P_{22}	376.98	376.63	378.23	535.04	379.94	432.77	406.31	379.67	449.04	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00
P_{23}	519.05	377.96	379.48	449.96	430.43	444.34	383.32	450.25	381.14	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00
P_{24}	388.12	379.74	377.68	502.64	381.12	376.41	380.99	375.94	379.48	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00
P_{25}	529.89	380.76	475.00	368.14	381.47	448.18	505.01	377.16	378.60	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00
P_{26}	382.01	378.46	417.66	453.88	378.51	378.40	377.79	450.54	379.88	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00
P_{27}	10.01	79.50	143.97	114.37	97.17	128.76	14.61	144.62	143.15	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P_{28}	21.09	146.39	48.51	11.21	110.67	74.47	127.51	87.89	73.80	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P_{29}	120.05	76.74	75.45	28.08	102.95	89.60	15.81	75.96	78.32	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P_{30}	86.79	94.98	94.04	90.70	93.26	92.92	96.80	94.49	94.46	97.00	97.00	97.00	97.00	97.00	97.00	97.00	97.00	97.00
P_{31}	186.80	186.42	188.00	188.65	186.51	187.59	184.68	186.73	187.78	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{32}	175.01	186.42	185.99	179.04	186.23	186.91	183.07	186.66	189.20	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{33}	187.29	186.42	185.87	175.25	186.25	188.94	186.93	186.14	185.98	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{34}	197.19	196.42	196.80	196.60	195.81	195.89	199.86	196.66	194.86	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00
P_{35}	197.10	196.42	196.76	194.61	196.33	196.92	199.78	196.67	195.87	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00
P_{36}	193.26	196.42	195.49	179.11	197.33	196.94	195.15	196.66	195.86	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00
P_{37}	105.68	106.42	105.80	101.07	106.31	106.57	97.64	106.66	106.79	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{38}	103.10	106.42	107.02	90.17	106.26	105.98	106.18	105.83	105.74	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{39}	104.43	106.42	106.98	105.93	105.94	108.10	108.87	107.21	104.33	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{40}	517.24	446.64	480.78	465.74	380.93	381.84	379.97	378.92	446.55	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00	550.00

Table A4. The results in terms of power output of GA and GA-ASA for ELD problem based on 40 Gus by considering VPLE.

GU	Variants of GA									Variants of GA-ASA								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
P_1	113.68	110.41	109.95	110.18	111.49	110.60	111.47	109.49	111.34	110.80	111.64	110.80	110.80	110.80	110.80	110.80	114.00	114.00
P_2	105.05	110.07	110.21	106.60	110.49	111.02	109.68	111.47	110.69	74.74	111.45	110.80	110.80	110.86	110.80	110.80	114.00	114.00
P_3	112.96	115.87	115.90	115.51	115.49	117.03	119.81	115.34	117.14	97.40	97.40	120.00	97.40	120.00	120.00	97.40	97.40	120.00
P_4	182.90	186.20	185.98	184.74	186.46	185.98	188.15	186.40	185.10	80.00	179.73	179.73	179.73	179.73	129.87	129.87	129.87	129.87
P_5	87.36	93.85	93.01	88.74	93.49	92.04	93.99	93.25	93.03	87.80	97.00	93.97	87.80	88.02	97.00	97.00	89.61	97.00
P_6	135.91	138.09	137.27	139.70	138.91	136.06	137.76	137.38	137.34	140.00	140.00	140.00	140.00	140.00	140.00	140.00	140.00	140.00
P_7	297.86	296.63	297.22	291.51	296.49	295.97	295.16	297.48	297.27	300.00	259.60	300.00	300.00	300.00	259.60	259.60	259.60	300.00
P_8	286.46	296.11	296.23	293.08	296.95	296.95	299.72	296.44	296.18	284.60	284.60	284.60	284.60	284.60	284.60	284.60	284.60	284.60
P9	292.44	295.94	296.09	292.58	296.49	295.00	295.54	296.43	297.21	284.60	284.60	284.60	284.60	284.60	284.60	284.60	284.60	284.60
P_{10}	294.94	296.13	297.10	292.90	296.49	295.97	299.84	297.32	295.14	130.00	130.00	130.00	130.00	204.80	130.00	130.00	130.00	130.00
P_{11}	371.15	371.40	370.20	360.53	371.45	371.01	370.85	371.49	371.81	318.40	243.60	243.60	318.40	318.40	243.60	168.80	318.40	243.60
P_{12}	371.40	371.11	372.54	367.15	371.49	371.03	371.52	372.65	370.58	318.40	168.80	318.40	318.40	318.40	168.80	243.60	243.60	168.80
P_{13}	399.82	376.82	384.39	374.27	380.05	380.11	396.77	433.54	378.18	214.76	394.28	304.52	214.76	125.00	394.28	394.28	304.52	394.28
P_{14}	481.35	432.68	381.55	391.22	378.74	381.36	383.99	423.66	378.53	304.52	484.04	214.76	214.76	214.76	304.52	394.28	304.52	304.52
P_{15}	386.83	385.23	378.29	388.42	380.58	376.28	363.82	377.95	379.36	304.52	304.52	214.76	125.00	214.76	304.52	394.28	394.28	304.52
P_{16}	372.68	381.30	379.76	382.01	377.51	378.40	385.30	400.05	377.84	304.52	304.52	394.28	304.52	214.76	304.52	394.28	394.28	304.52
P_{17}	463.13	379.69	445.59	385.09	447.68	380.45	364.38	378.89	380.59	489.28	489.28	399.52	489.28	489.28	399.52	399.52	399.52	489.28
P_{18}	475.03	399.82	379.05	374.55	379.97	380.52	379.84	380.68	446.02	399.52	489.28	399.52	489.28	489.28	489.28	399.52	399.52	489.28
P_{19}	425.57	381.54	378.96	375.22	448.88	377.49	352.18	380.83	380.52	511.28	511.28	511.28	511.28	511.28	511.28	511.28	511.28	511.28
P_{20}	378.68	381.34	381.07	373.04	380.29	377.53	396.67	380.00	400.84	511.28	331.76	511.28	511.28	511.28	511.28	421.52	511.28	421.52
P_{21}	377.41	380.08	439.15	370.32	437.23	452.26	480.10	456.86	380.07	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28
P_{22}	342.65	434.14	379.78	465.87	376.55	380.39	468.39	380.57	379.76	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28
P_{23}	391.60	381.49	378.17	377.86	440.41	379.27	464.56	378.00	377.77	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28	433.52
P_{24}	393.98	376.72	381.54	507.85	378.21	380.59	330.46	425.23	438.45	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28
P_{25}	368.35	425.73	379.82	548.74	378.85	515.41	397.21	382.00	433.57	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28
P_{26}	461.86	449.35	438.72	465.38	379.02	443.31	376.78	377.87	433.30	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28
P_{27}	49.89	73.79	144.05	30.29	87.85	145.04	133.03	97.64	144.74	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P_{28}	65.97	145.56	83.78	10.17	145.49	71.17	41.40	91.42	83.62	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P_{29}	89.52	92.16	78.36	125.37	74.08	80.78	28.40	122.94	76.59	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P_{30}	94.65	94.16	92.68	90.81	93.44	93.00	90.98	93.23	92.24	87.80	97.00	87.80	96.34	88.41	90.56	97.00	89.51	97.00
P_{31}	184.57	186.59	186.48	186.51	187.07	186.04	182.93	186.49	187.55	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{32}	185.05	185.91	186.17	179.94	186.46	187.06	188.10	188.76	187.68	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{33}	183.89	185.79	187.22	189.30	186.42	188.99	184.83	186.49	187.65	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{34}	193.83	195.58	196.13	192.41	196.49	197.92	197.64	197.29	196.16	164.80	164.80	164.80	200.00	200.00	200.00	164.80	164.80	166.11
P_{35}	197.01	195.11	197.21	189.09	196.49	195.96	194.90	197.35	197.38	200.00	164.80	200.00	200.00	200.00	164.80	180.96	164.80	200.00
P_{36}	193.84	198.03	195.29	194.34	196.46	195.90	194.88	196.04	196.24	200.00	164.80	200.00	200.00	200.00	164.80	200.00	164.80	200.00
P_{37}	105.95	107.12	105.70	96.74	106.49	105.93	103.50	106.36	106.24	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{38}	102.44	105.85	106.17	109.72	108.49	107.05	104.41	109.46	109.56	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{39}	101.25	106.69	106.23	108.49	106.49	106.02	108.97	106.32	105.99	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{40}	381.10	379.94	446.98	373.77	378.62	377.08	512.12	378.97	380.74	511.28	421.52	511.28	511.28	511.28	511.28	421.52	421.52	511.28

Table A5. Results in terms of power output of GA and GA-ASA for ELD problem based on 40 GUs by considering VPLE-SW.

GU	Variants of GA									Variants of GA-ASA								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
P_1	110.26	110.45	110.13	112.61	110.43	111.72	112.49	109.63	110.34	110.80	114.00	111.45	110.80	110.80	110.80	110.80	110.80	114.00
P_2	111.49	110.48	110.74	110.31	110.47	110.35	110.30	110.00	110.56	110.80	114.00	113.19	110.80	110.80	110.80	110.80	110.80	114.00
P_3	109.77	116.48	116.09	119.48	116.43	116.42	113.09	116.19	116.56	97.40	120.00	60.00	97.40	120.00	97.40	60.00	97.40	120.00
P_4	182.09	186.48	185.16	188.68	186.41	186.35	184.80	185.85	185.01	179.73	179.73	183.85	179.73	179.73	179.73	179.73	179.73	179.73
P_5	91.58	93.48	92.90	91.34	91.43	92.81	87.76	92.92	92.06	91.85	97.00	87.81	96.34	87.80	87.80	87.80	87.80	97.00
P_6	136.59	136.48	136.13	137.04	136.43	135.42	131.93	135.94	136.12	140.00	140.00	140.00	140.00	140.00	140.00	140.00	140.00	140.00
P_7	298.14	297.48	295.99	295.65	296.38	296.29	292.16	295.66	295.97	259.60	300.00	300.00	300.00	300.00	300.00	259.60	300.00	300.00
P_8	288.10	296.48	296.76	298.96	296.43	296.29	296.05	296.90	295.93	284.60	300.00	210.03	284.60	284.60	284.60	284.60	284.60	300.00
P9	289.65	296.42	296.56	299.71	296.43	296.92	297.07	295.93	295.02	284.60	290.17	284.63	284.60	284.60	284.60	284.60	284.60	300.00
P_{10}	291.58	296.48	294.19	297.20	296.43	296.26	292.12	296.07	293.97	204.80	130.00	130.00	279.60	130.00	130.00	204.58	130.00	204.80
P_{11}	372.69	371.48	371.83	373.94	372.43	372.51	374.94	370.92	370.94	168.80	318.40	318.36	168.80	318.40	243.60	242.76	318.40	318.40
P_{12}	368.51	371.48	370.93	372.39	371.37	371.17	370.26	370.81	371.01	168.80	168.80	168.94	318.40	318.40	168.80	242.17	318.40	168.80
P_{13}	375.69	378.37	378.04	381.17	376.59	377.61	383.10	378.37	379.48	304.52	304.52	304.50	304.52	304.52	304.52	394.28	214.76	214.76
P_{14}	372.98	380.93	379.57	380.50	381.71	382.50	373.85	377.10	380.83	394.28	394.28	394.30	214.76	214.76	394.28	304.52	304.52	304.52
P_{15}	373.65	379.99	380.66	420.85	377.97	383.71	371.95	379.83	379.56	394.28	394.28	394.28	394.28	214.76	394.28	394.28	304.52	304.52
P_{16}	497.71	377.12	378.40	382.99	378.03	376.40	382.64	379.61	380.65	484.04	304.52	214.76	304.52	214.76	394.28	394.28	304.52	394.28
P_{17}	377.78	378.04	380.58	375.72	379.20	380.95	388.07	378.30	381.69	489.28	399.52	399.50	399.52	489.28	399.52	399.52	399.52	399.52
P_{18}	385.98	379.72	380.35	396.43	378.49	378.56	370.27	378.25	383.99	489.28	399.52	489.28	399.52	489.28	399.52	399.52	489.28	399.52
P_{19}	369.66	380.14	376.71	383.11	376.05	380.13	514.11	381.48	380.53	421.52	511.28	421.55	511.28	421.52	511.28	511.28	511.28	511.28
P_{20}	510.86	514.48	381.93	418.77	377.37	379.99	378.16	421.36	380.39	421.52	421.52	511.29	421.52	511.28	511.28	421.52	511.28	421.52
P_{21}	507.27	377.87	379.89	374.86	514.91	378.18	386.26	384.22	378.25	523.28	433.52	523.31	523.28	523.28	433.52	523.28	523.28	438.64
P_{22}	359.22	512.72	385.18	494.32	386.84	379.08	442.63	421.33	381.37	433.52	523.28	523.30	433.52	523.28	433.52	523.28	523.28	523.28
P_{23}	377.36	380.61	382.38	392.60	516.35	375.06	439.89	378.91	513.87	433.52	433.52	523.27	523.28	523.28	523.28	523.28	523.28	523.28
P_{24}	382.14	376.36	378.39	381.61	378.81	516.50	523.65	474.95	379.06	523.28	523.28	523.28	523.28	523.28	523.28	523.28	433.52	523.28
P_{25}	369.11	377.69	379.76	378.90	378.52	383.25	387.77	476.45	378.13	433.52	523.28	523.29	523.28	523.28	523.28	523.28	523.28	523.28
P_{26}	491.53	382.72	517.24	336.93	378.61	378.28	369.65	378.45	380.07	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28	523.28
P_{27}	93.45	93.48	92.83	92.98	93.43	94.42	93.58	92.49	93.10	87.80	97.00	87.89	87.80	87.80	87.80	87.80	47.00	97.00
P_{28}	182.05	186.33	185.87	183.07	186.43	185.37	182.88	185.91	184.05	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{29}	186.87	186.43	186.05	186.34	186.44	187.64	187.78	186.05	185.87	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{30}	189.23	186.47	185.33	186.56	186.43	185.37	181.57	185.14	187.15	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00	190.00
P_{31}	199.59	196.47	195.85	199.89	196.43	197.29	196.01	196.80	196.10	200.00	200.00	193.39	200.00	185.94	164.80	164.80	164.80	200.00
P_{32}	194.80	194.73	194.75	198.31	197.43	195.97	195.80	196.88	196.32	200.00	200.00	200.00	200.00	200.00	198.88	164.80	194.80	200.00
P_{33}	191.83	197.48	196.88	199.74	195.43	195.41	196.11	196.63	196.16	200.00	200.00	200.00	200.00	200.00	200.00	164.80	200.00	200.00
P_{34}	104.06	106.45	107.13	104.28	106.43	106.42	106.60	105.88	106.07	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{35}	104.09	107.43	106.76	105.89	106.43	106.29	98.74	105.98	105.74	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{36}	107.07	106.41	105.67	109.77	106.43	107.29	102.26	106.43	108.01	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00	110.00
P_{37}	377.79	378.89	515.38	505.45	377.28	512.67	381.81	377.41	514.16	511.28	511.28	511.26	511.28	511.28	511.28	421.52	511.28	511.28
P_{38}	25.70	144.48	142.06	89.64	146.43	143.89	10.08	145.00	143.06	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P_{39}	10.00	144.48	138.94	125.33	144.43	139.23	123.60	105.01	142.86	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
P_{40}	132.07	10.04	10.02	16.68	10.00	10.04	68.18	48.95	10.01	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00

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