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Optimization of a typical biomass fueled power plant using Genetic Algorithm and Binary particle swarm optimization.

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Abstract:

Over thousands tons of animal manures are produced in Iran. The major animal manures producers are located in central regions. Animal manures collection is an autochthonous and important renewable energy sources that in most cases are released in nature by ranchers.

In this paper , a typical animal manure producer region is considered and optimal location and size of a typical biomass fueled power plant is determined.

Genetic algorithm (GA) is used as the major approach of determination and effectively this approach will make possible to determine the optimal location, biomass supply area and power plant size that offer the best profitability for investor. Binary particle swarm optimization algorithm is also used as the second approach of optimization and eventually results obtained from both algorithm are compared.

In this work we use profitability index (PI) as the fitness function of Genetic algorithm and the point with the maximum PI is selected.

Nomenclature

C_c	annual collection biomass cost (Rls/yr)	I_s	specific investment (Rls/MWh)
C_t	annual transport biomass cost (Rls/yr)	C^{cui}	unit collection biomass cost (in parcel i) (Rls/t)
E_g	annual energy production (MWh/yr)	P	unit parcel where the plant is installed (–)
r_c	annual increase rate of C_c (–)	C^{tui}	unit transport biomass cost (in parcel i) (Rls/t km)
r_{mo}	annual increase rate of C_{mo} (–)	U_i	usability coefficient of parcel i (–)
r_{mo}	annual increase rate of C_t (–)	V_u	useful lifetime (yr)
C_{mo}	annual M&O cost (Rls/yr)	L_x,L_y	X- and Y-dimensions (–)
T	annual plant running time (h/yr)	P_e	installed power (MW)
S_i	area of parcel i (km^2)	LHV_i	lower heating value in parcel i (MWh/t)
m	average maintenance cost (Rls/MWh)	D_i	net density of dry biomass in parcel i (t/km^2 yr)
dist(p,i)	distance between parcel i and p (km)	NPV	net present value of the investment (Rls)
P_L	electric line cost (Rls/km)	PV	present Value (Rls)
C_{mof}	fixed annual cost of M&O (Rls/yr)	PV_{in}	present value of cash inflows (Rls)
INV_f	fixed investment (Rls)	PV_{out}	present value of cash outflows (Rls)
η	gasifier–gas turbine global efficiency (–)	PI	profitability Index (–)
INV	initial investment (Rls)	P_g	selling price of the electric energy (Rls/MWh)

1. Introduction

The ever increasing growth of electric energy consumption has provided energy crisis in the world. The production of animal manure is rapidly increasing in Iran. Thousands number of tame animals produce thousands tons of animal manures which can be used to generate electrical energy [1]. It is usually mentioned that renewable energy sources (RES) have a large potential to contribute to the sustainable development of specific territories by providing them with a wide variety of socioeconomic benefits, including diversification of energy supply, enhanced regional and rural development opportunities, creation of a domestic industry and employment opportunities [2].

The global production of liquid biofuels is now estimated to be over 35mm^3. Ethanol currently accounts for more than 90% of total biofuel production. Global fuel ethanol production more than doubled between 2000 and 2005, while production of biodiesel, starting from a much smaller base, expanded nearly fourfold. Some examples: Brazil has exported in 2004 2.5 billion litres of ethanol (same in 2005) with main destinations India (23.1%) and USA (20.2%) [3].

There are several options to produce electricity from biomass:

Combustion, gasification and pyrolysis, gasification being the most efficient one[4]. Gasification of biomass is a thermal treatment, which ensues in a high production of gaseous products and small amounts of char and ash. Steam reforming of hydrocarbons, partial oxidation of heavy oil residues, selected steam reforming of aromatic compounds, and gasification of coals and solid wastes to yield a mixture of H2 and CO, accompanied by water–gas shift conversion to produce H2 and CO2, are well-proved processes . Also, the use of animal manure, like that of any other biomass, can contribute to sustainable development in rural areas[5,6].

Pyrolysis has been applied for thousands of years for charcoal production but it is only on the last 30 years that fast pyrolysis at moderate temperatures of around 500 _C and very short reaction times of up to 2 s has become of considerable interest. This is because the process directly gives high yields of liquids of up to 75 wt.% which can be used directly in a variety of applications [1] or used as an efficient energy carrier[7].

Chemically, bio-oils consist of hundreds of organic compounds, including many valuable chemicals. However, most of the chemicals are in low contents, making their recovery not only technically difficult but also economically unattractive at present[8].

In the future, biomass combustion will play an important role in energy production to obtain electricity or heating. But the variability in properties of biomass fuels is great and may significantly influence the efficiency and environmental impacts associated with their utilization [9-10].

In the field of biomass power plants , its very important to optimize the plant size and location. This optimization process is done via different optimization algorithms. authors as Lopez and et al have compared metaheurestic techniques of determining optimal location and size of biomass power plants. They have used four metaheurestic techniques to find optimal lolcation , size and supply area of a typical biomass fueled power plant inside a region of 32000 km^2 covered with natural forest vegetations[11].

Lopez and et al have also proposed individual particle swarm optimization to find optimal location , supply area and plant size in a region of 1024 square kilometers covered with natural forest vegetations[12].

In a different work , Jurado and Cano have studied on optiml placement of biomass fueled gas turbine. as opposed to previous works ,beside economical constraints , loss reduction plays more important role to find the optimum placement and plant size[13].

In particular, Taleghan is a Iran Town in Alborz province. The agricultural economy mainly works with cattle ranching. This region is divided in 72 parcels of different surface S_i. The extension is 1400 km^2 approximately.

In this work, we will investigate the region and determine the optimal location , supply area and size of a typical biomass fueled power plant using two metaheuristic technique, GA and BPSO . animal manures are used as the plant input feedstock and gasification being the major conversion process .

2. Optimization problem

2.1. Problem description

The problem to be solved consists of determining the optimum location , size and supply area of a biomass-fueled power plant based on animal manures. For such goal, 2 metaheuristic techniques are applied and compared. Here, we have employed two population-based methods (GA and BPSO). The size of the generation system depends on:

1. biomass quantity that can be collected,
2. selection of parcels where to collect the biomass.
3. The technology used to convert biomass to electrical energy.

Placement of power plant (parcel p) mainly depends on the characteristics of the parcels. In this work, K parcels of different area have been considered, all of them characterized by a predominant biomass type (animal manure). These parcels also present other relevant characteristics, such as accessibility.

The values of the variables involved in the problem are obtained from databases or Geographic Information Systems (GIS). These are the following:

- Si: Area of parcel i (km^2)
- Ui: Usability coefficient of parcel i. It is applied to only take the usable surface into account.
- Di: Net density of dry biomass yield from parcel i ($ton/km^2.yr$).
- LHVi: Lower heat value of biomass in parcel i (MW h/ton).
- Lp: Length of the electric line that connects the power plant to the grid (km).
- Dis (p; i) , Distance between parcel i and the power plant, which is located in parcel p(km).
- C^{cui} : Biomass collection unit cost in parcel i (Rls/ton).

Therefore, assuming the total mean efficiency of the gas turbine g, the electricity produced, Eg (MW h/yr), equals to:

$$E_g = \eta.\sum_{i=1}^{k} S_i.U_i.D_i.LHV_i \qquad (1)$$

Assuming a plant operating time of T(h/yr), the installed power, Pe (MW), is:

$$P_e = \frac{E_g}{T} \qquad (2)$$

2.2. Objective fitness function , profitability index

The objective fitness function takes costs and benefits into account. Particularly , initial investment and collection, transportation, maintenance and operation(M&O) costs are intended, against to benefits from the sale of electrical energy. thus, the profitability index is selected as the objective function. In this section some interesting parameters to evaluate the profitability index of the project are reviewed. The initial investment, the present value of cash inflows (benefits) and cash outflows (costs) and the net present value are studied and adapted to the particularities of this work.

2.2.1. Initial investment

The initial investment (INV) consisting of design , construction and equipment of the biomass power plant is expressed as:

$$INV = INV_f + I_s.P_e + C_L.L_p \qquad (3)$$

Where INV_f is the fixed investment (Rls) , I_s is the specific investment (Rls/mw) and C_L is the electric line cost (Rls/km).

2.2.2. Cash inflows

The present value of cash inflows (PV_{in}) is gained from the sold electric energy during the useful lifetime, V_u. It can be written as:

$$PV_{in} = P_g.E_g.\frac{K_g.(1-K_g^{Vu})}{1-K_g} \qquad (4)$$

Where p_g is the selling price of electric energy injected to the network (Rls/mwh) , E_g the sold and produced electric energy (Mwh/yr) , and $K_g = \frac{1+r_g}{1+d}$, r_g being the annual increase rate of the sold energy price and d the nominal discount rate.

2.2.3. Cash outflows

The present value of cash outflows (PV_{out}) is the sum of the following costs during the useful lifetime of the plant:

Annual collection cost, C_c, annual transport cost, C_t, and annual M&O costs, C_{mo}. The annual cost of biomass collection is:

$$C_c = \sum_{i=1}^{k} (C_{cu_i}.U_i.S_i.D_i) \qquad (5)$$

The annual cost of biomass transport is:

$$C_t = \sum_{i=1}^{k} (C_{tu_i}.U_i.S_i.D_i.dist(p,i)) \qquad (6)$$

The annual M&O cost is :

$$C_{mo} = C_{mof} + m.E_g \qquad (7)$$

Finally, the present value of cash outflow is :

$$PV_{out} = C_c.\frac{K_C.(1-K_C^{VU})}{1-K_c} + C_t.\frac{K_t.(1-K_t^{VU})}{1-K_t} + C_{mo}.\frac{K_t.(1-K_{mo}^{VU})}{1-K_{mo}} \qquad (8)$$

Where :

$$K_c = \frac{1+r_c}{1+d} \text{ , } K_t = \frac{1+r_t}{1+d} \text{ , } K_{mo} = \frac{1+r_{mo}}{1+d}$$

2.2.4. Net present value

The net present value (NPV) of an investment is defined as:

$$NPV = PV - INV \qquad (9)$$

$PV = PV_{in} - PV_{out}$ being the present value. An investment is profitable when NPV>0.

2.2.5. Profitability index

The Profitability Index (PI) is chosen in this work as objective fitness function. It is defined as follows:

$$PI = \frac{NPV}{INV} = \frac{PV}{INV} - 1 \qquad (10)$$

We can also say that an investment is profitable when PI > 0.

3. Metaheurestic

In this section we briefly describe two main metaheurestic algorithms applied in this work. As demonstrated in [17] population methods utilized in this work (GA and BPSO) are more efficient than trajectory algorithms (SA, TB or fuzzy search).

3.1. Binary particle swarm optimization

The common version of the particle swarm optimization proposed via Kennedy and Eberhart[14] , operates in a continuous search space. In order to solve optimization problems in discontinues and discrete search spaces, several binary discrete PSO algorithms have been introduced. In a discrete binary search space the position of a particle is depicted by a N-length bit string and the movement of the particle consists of flipping some of these bits.

In this work, we have presented an improved version of the binary PSO algorithm proposed in[14] , which incorporates a inertia weight factor, like the classical continuous approach. Now, particle position (xi) and particle velocity (vi) are Nlength binary vectors. The algorithm uses the Hamming distance, and the logical AND ('_'), OR (' + ') and XOR ('') operators. Particle position is updated by using the XOR operator instead of the sum-operator, as in[15-16].

$$x_{ij}^{t} = x_{ij}^{t-1} \oplus v_{ij}^{t-1} \quad , i=1,....p, j=1,....p \qquad (11)$$

Z represents the number of variables of the function to be optimized and P the number of particles in the swarm.In this algorithm, the velocity vector can be interpreted as a change vector[18]. Thus, if $v_{ij}^{t}="1"$, then $x_{ij}^{t} = \overline{x_{ij}^{t-1}}$ being the logical negation of x_{ij}^{t-1}. However if $v_{ij} = '0'$, then $x_{ij}^{t} = x_{ij}^{t-1}$ (no change happens). The velocity vector (change vector) is updated by applying the following equation [17-18]:

$$v_{ij}^{t} = \overline{\omega_{ij}} + \omega_{ij}.(c1_{ij}.(pbest \oplus x_{ij}^{t-1}) + c2_{ij}.(gbest_{j}^{t-1} \oplus x_{ij}^{t-1}) \qquad (12)$$

Where

- $C1_i=[C1_{i,1},\ldots\ldots C1_{i,n}]$ and $C2_i=[C2_{i,1},\ldots\ldots\ldots\ldots\ldots C2_{i,n}]$ are random Nlength binary strings, whose components have the same probability.
- $pBest_i^{t-1}=[pBest_{i,1}^{t-1},\ldots\ldots\ldots\ldots pBest_{i,n}^{t-1}]$, $gbest_i^{t-1}=[gBest_1^{t-1},\ldots\ldots\ldots, gBest_n^{t-1}]$ are also N-length binary strings.
- $\omega_i = [\omega_{i,1},\ldots\ldots\ldots\ldots\ldots\omega_{i,n}]$ is the inertial vector of the ith particle. It is a random N-length binary vector, whose components are '0' with probability P_ω.
- $\overline{\omega_i} = [\overline{\omega_{i,1}},\ldots\ldots\ldots\overline{\omega_{i,n}}]$ is the one's complement of inertial vector ω_i.

The inertial probability , P_ω is a very important parameter in BPSO . as just mentioned , bits in ω_i are '0' with probability P_ω . Inertial probability decreases with the number of iterations, in such a way that at the initial iterations (high Px values) the algorithm explores the search space and at the last iterations (low Px values) the algorithm exploits the search space.It must be noted that if xi;j = '0', then vti ;j = '1', and so position of the ith particle is changed. However, if xi;j = '1', the movement of the ith particle at the tth iteration is conducted by pbestt_1 i and gbestt_1 solutions, with a partially stochastic behavior due to the random learning vectors c1i and c2i. The idea is to allow particle swarm to perform a random exploration over the space search at the initial iterations. Later, when the swarm has acquired enough knowledge about the problem, the movement of each particle is mainly conducted by pbesti and gbest solutions[19-22].

3.2. Genetic algorithm

The genetic algorithm is a search heuristic that mimics the process of natural evolution. Physics, Biology, Economy or Sociology often have to deal with the classical problem of optimization. Purely analytical methods widely proved their efficiency. They nevertheless suffer from a insurmountable weakness : Reality rarely obeys to those wonderful differentiable functions your professors used to show you. They are general purpose search algorithms that use principles inspired by natural genetics to evolve solutions to problems. A GA starts off with a population of randomly generated chromosomes, and advances toward better chromosomes by applying genetic operators. During successive iterations, called generations, chromosomes in the population are rated for their adaptation as solutions.

On the basis of these evaluations, a new population of chromosomes is formed using a selection mechanism and specific genetic operators, such as crossover and mutation. An evaluation or fitness function must be devised for each problem to be solved.

Given a particular chromosome (a possible solution), the fitness function returns a single numerical value, which is supposed to be proportional to the utility or adaptation of the solution represented by that chromosome[23].

Although there are many possible variants GA, the underlying mechanism operates on a population of chromosomes or individual, and consists of three operations:

- Evaluation of individual fitness. For each problem to be solved, a suitable fitness function is required.
- Formation of a gene pool through selection mechanisms. Here, the so-called elitist strategy has been used in order to include into the gene pool the best found solutions.
- Recombination through crossover and mutation operators. In this work, single point crossover is performed, and an exponentially decreasing function is used for the mutation probability.

GA are especially well-fitted to difficult environments where the space is usually large, discontinuous, complex and poorly understood.

It is generally accepted that application of GA must take into account the following components[24]:

- A genetic representation of solutions to the problem.
- A way to create an initial population of solutions.
- An evaluation function, which gives the fitness of each chromosome.
- Genetic operators, which modify the genetic composition of offspring during reproduction.
- Values for the parameters of the GA (population size, probabilities of applying genetic operators, etc.).

4. Experimental results

The region under study is consisting of 72 parcels with different surfaces. Each parcel is covered with animal manures that can be used as a useful biomass type. The required information for each parcel consists of D_i , U_i , S_i , LHV_i , L_p , Dis(P,i) , C^{cui} , C^{tui} , C^{mo} .

All of parcels are covered with electrical network so that no electrical line cost is needed to connect the plant to the network. The single line diagram of electrical network is shown in fig.1.

the theoretical biomass potential, which is defined from the net density of dry biomass that can be obtained at any parcel, Di (t/(km2 yr)), and provides a measure of the primary biomass resource and also the available biomass potential. It has been created taking the following parameters into account: Di (t/(km2 yr)), Ui, Si (km2) and LHVi (MWh/t). Multiplying the four variables for all parcels that comprise the entire region, it results the available biomass potential, expressed in (MWh/yr) are shown in table 1.the Geographical representation of parcels are shown in fig.2.

Fig.1: Region under study and location of electrical lines.

Table 1:theoretical and available biomass potential

Parcel no (i)	Available potential(mwh/yr)	theoretical potential(t/yr)	Parcel no (i)	Available potential(mwh/yr)	theoretical potential(t/yr)
37	1.752	1.752	1	290.97216	84.96
38	122.64	122.64	2	129.32096	37.37
39	40.296	40.296	3	681.966	197.1
40	6.061	1.752	4	11802.5	3411.44
41	49.056	49.056	5	3728.0808	1077.14
42	170.82	170.82	6	2192.3944	633.44
43	255.792	255.792	7	2192.3944	633.44
44	94.608	94.608	8	697.12	201.48
45	3.504	3.504	9	144.48	40.88
46	7.008	7.008	10	60.6192	11.52
47	12.264	12.264	11	1768.06	511
48	32.704	32.704	12	6.06192	. 1.752
49	182.208	182.208	13	6.06192	1.752
50	5.84	5.84	14	774.91544	223.96
51	1.752	1.752	15	367.75648	106.28
52	5.84	5.84	16	15.1548	4.38
53	10.512	10.512	17	636.5016	183.96
54	0.584	0.584	18	945.65952	273.31
55	0.292	0.292	19	80.8256	23.36
56	7.3	7.3	20	373.8184	107.14
57	0.292	0.292	21	40.4128	11.68
58	4.672	4.672	22	80.8256	11
59	29.2	29.2	23	169.73376	49.056
60	7.008	7.008	24	1.01032	0.292
61	29.2	29.2	25	113.15584	32.704
62	0.584	0.584	26	6.06192	1.752
63	56.94	56.94	27	113.15584	32.704
64	9.344	9.344	28	48.49536	14.016
65	11.68	11.68	29	636.5016	183.96
66	55.48	55.48	30	1348.7772	389.82
67	87.6	87.6	31	557.69664	161.184
68	5.84	5.84	32	1202.2808	347.48
69	44.384	44.384	33	40.4128	11.68
70	16.06	16.06	34	151.548	43.8
71	56.064	56.064	35	210.14656	60.736
72	827.82	827.82	36	72.74304	21.024

Simulation results for Genetic algorithm consisting of optimal location , supply area , installed power and profitability index is compared with BPSO algorithm. Required parameters for BPSO and GA optimization are
Shown in table2.

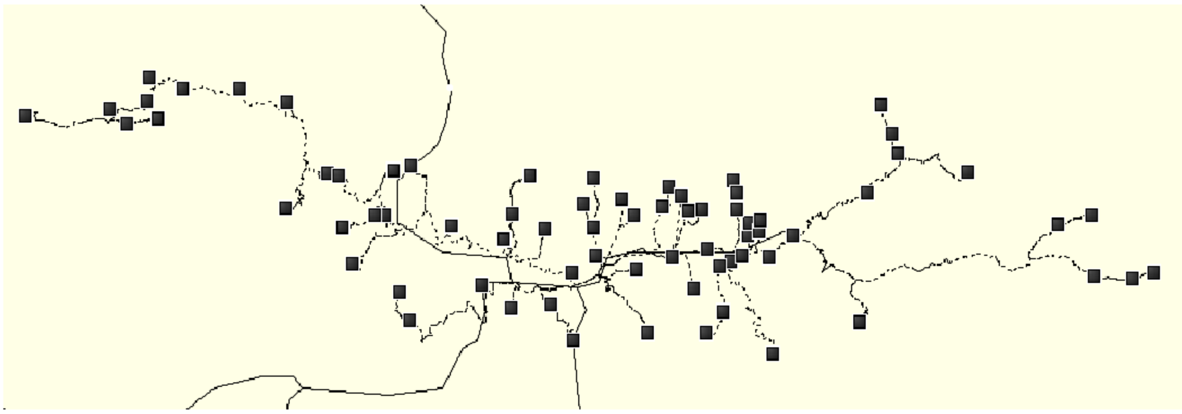

Fig2. the geographical position of parcels in the region under study.

Table 2: estimated values of parameters

parameter	value	parameter	value
C^{tui}(Rls/t.km)	10^5	r_c	0.1
C^{cui}(Rls/ton)	2×10^5	r_t	0.1
C_L(Rls/km)	25×10^6	r_{mo}	0.12
T(h/yr)	7500	C_{mof}(Rls)	2×10^9
INV_f(Rls)	2×10^9	M(Rls/mwh)	1.2×10^5
P_s(Rls/mwh)	1300	η	0.4
DR	0.08	I_s(Rls/mw)	2×10^{10}
IR	0.1	V_u(yr)	15

As is shown in figure 2, the search space consists of 72 individual parcels. The simulation parameters for BPSO and GA algorithms are shown in Table2. to start simulation ,two technical constraints are applied. the first simulation will start with the following technical constraints:

1. The electric power generated by the plant is limited to 2 MW.
2. The plant must be supplied via optimized parcels.

In Iran electric energy price for a plant Pe≤2 Mw is 1300 Rls/kwh. Since the plant is supplied via discreet biomass centers, supply area is consisting of several parcels inside an optimum area.
The optimal location and supply area of the best found profitability index for GA and BPSO for Pe=2MW is shown in figures 3 and 4 respectively. and also the output value of both algorithms (GA and BPSO) are shown in table3. Average profitability index evolution for GA and BPSO is shown in figure 5.

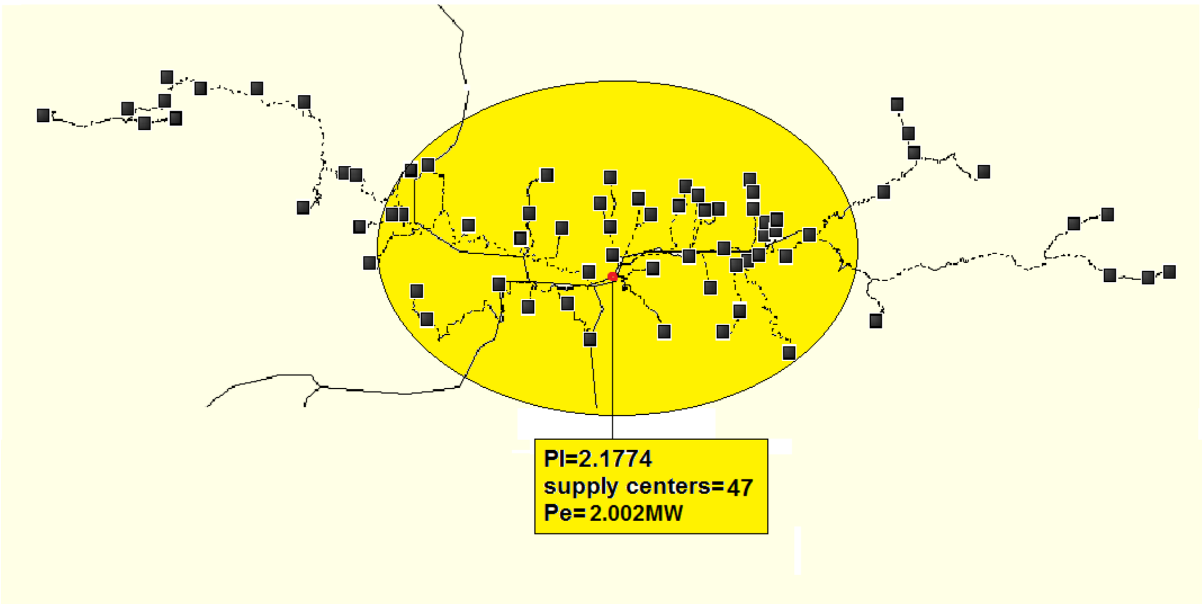

Fig.3: optimal location and supply area of biomass power plant for Genetic algorithm (Pe=2 mw)

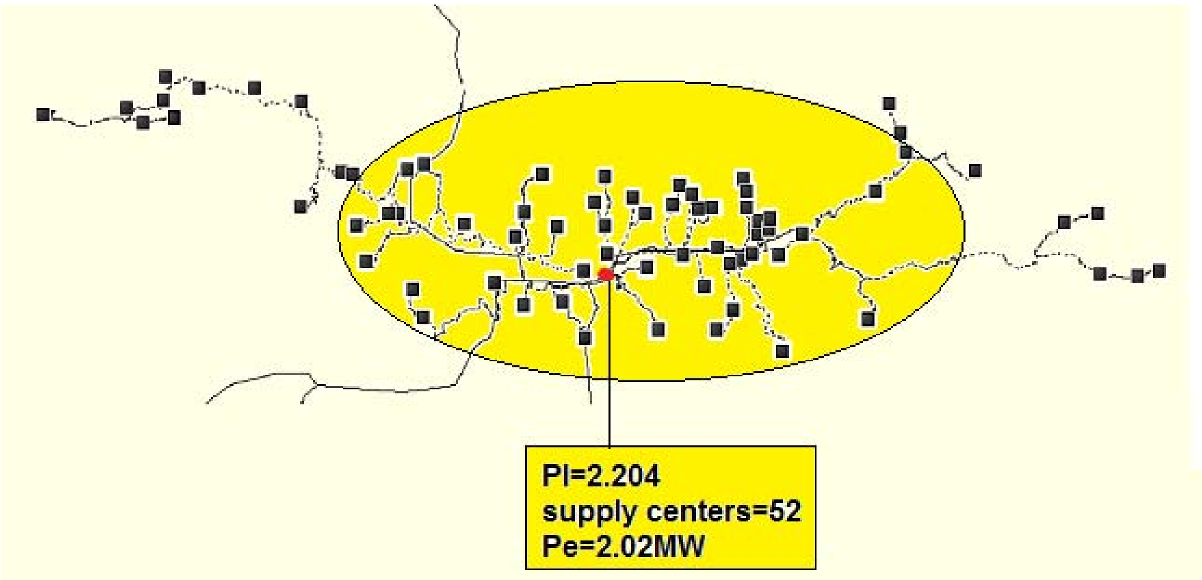

Fig.4: optimal location and supply area of biomass power plant for binary particle swarm optimization (Pe=2 mw)

Table 3: GA versus BPSO simulation results

algorithm	Pe(MW)	PI	Location coordinate	Supply centers
GA	2	2.177	L_x=478962 , L_y=4003802	47
BPSO	2	2.204	L_x=478962 , L_y=4003802	52

Looking at figure 5 shows that GA is rapidly converged while BPSO has higher profitability index than GA. the optimum location is the same for both algorithms. The supply centers inside the optimum area are 47 for GA and 52 for BPSO.

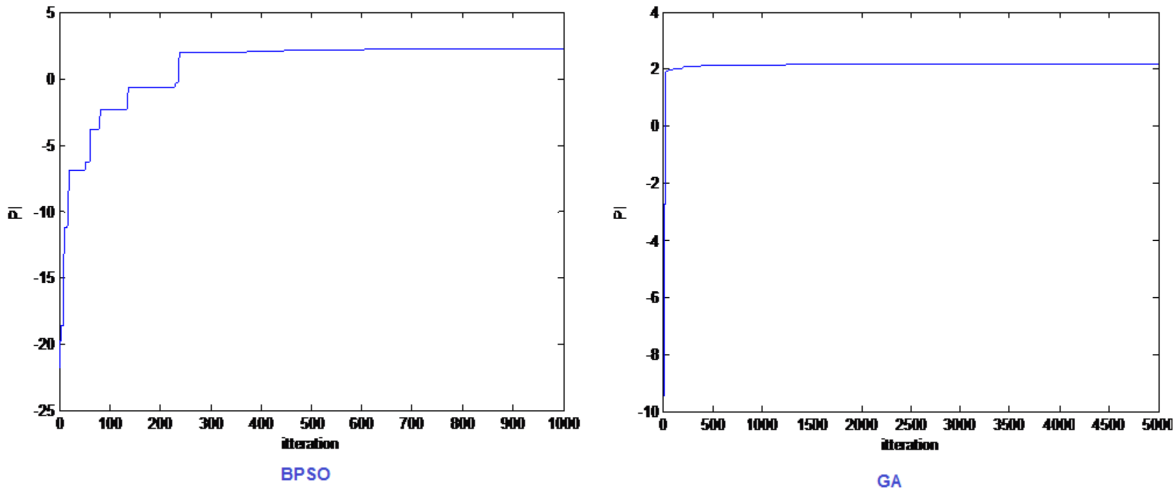

Fig.5: average profitability index versus iteration for GA and BPSO (Pe=2MW)

the second simulation will start with the following technical constraints:

1. The electric power generated by the plant is limited to 1 MW.
2. The plant must be supplied via optimized parcels.

The optimal location and supply area of the best found profitability index for GA and BPSO for Pe=1MW is shown in figures 3 and 4 respectively. the output values are also shown in table 4. . Average profitability index evolution for GA and BPSO is shown in figure 7.

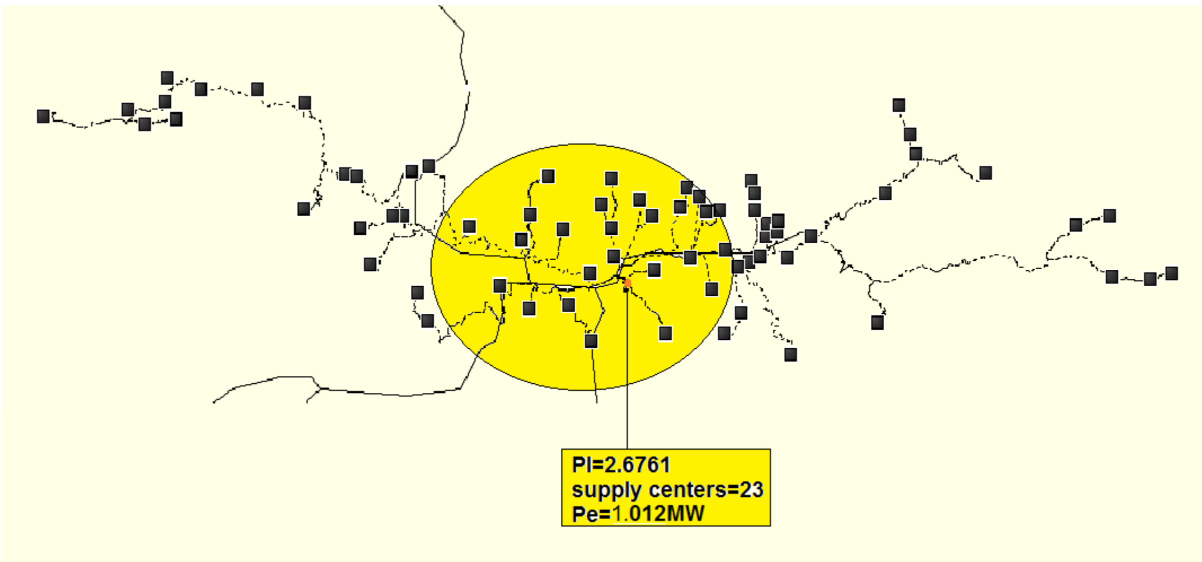

Fig.6: optimal location and supply area of biomass power plant for GA and binary particle swarm optimization (Pe=1MW)

Table 4: GA and BPSO simulation results(Pe=1 MW)

algorithm	Pe(MW)	PI	Location coordinate	Supply centers
GA and BPSO	1	2.6761	L_x=481499, L_y=4002736	23

The second simulation (Pe=1 MW) has the same results for the both algorithms. the only difference here is that the Ga is more rapidly converged and has lower simulation time than BPSO.the profitability index in this case is higher than first simulation.

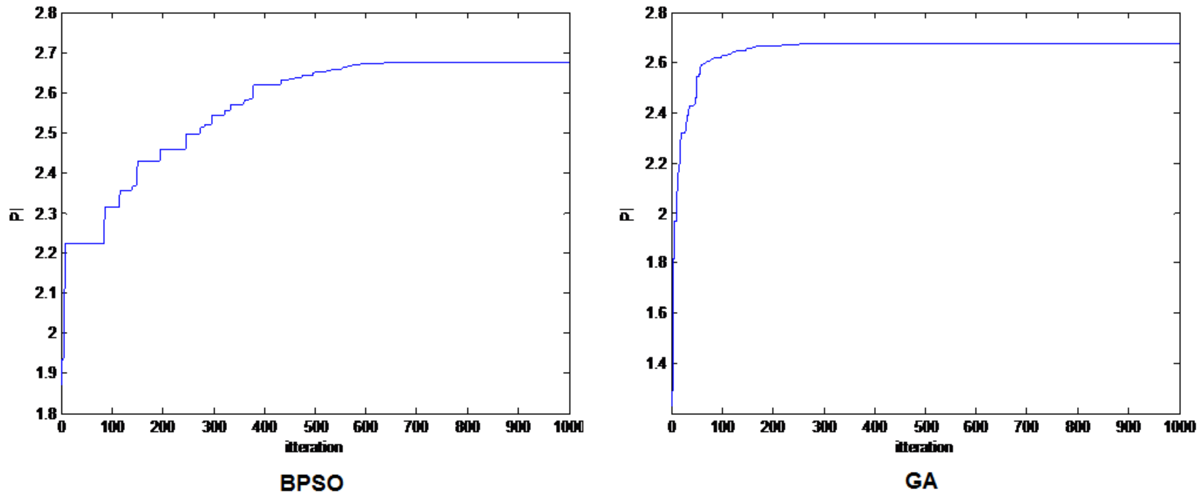

Fig.7: average profitability index versus iteration for GA and BPSO (Pe=1 MW)

5. Conclusion

The aim of this paper is to find optimal location, size and supply area of a typical biomass fueled power plant in a typical region In Iran. The region under study is approximately 1400 km^2 and is consisting of 72 parcels with different surfaces S_i. each parcel is covered with tame animal manure that can be converted into electrical energy.

There are Several options to covert biomass into electrical energy. Gasification, pyrolysis and combustion are the most popular of them.

all of our experiments show that the optimal plant size according to profitability index is 1.012 MW (PI=2.6761). The best locations corresponds to coordinate X=481499 and Y=4002736 (fig. 6).the simulation results for 2MW case shows that the profitability index in this case is lower than 1 MW. the plant won't be profitable if Pe≤0.4 MW.the profitability versus installed power characteristics is shown in figure 7. As is shown in this figure , maximum profitability index is achieved in Pe=1MW.

Here , GA and BPSO are the metaheuristics techniques applied to optimization problem. As experiments show, due to discreet search space, GA is rapidly converged an has lower simulation time than BPSO (figures 5 and 7).

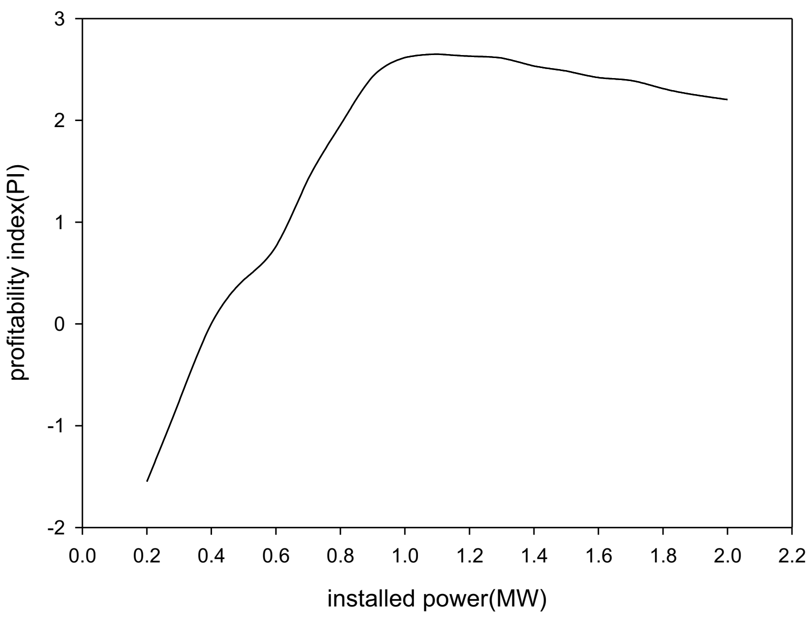

Fig.7: the profitability versus installed power

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