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Comparing supply side and demand side options for electrifying a local area using life cycle analysis of energy technologies and demand side programs

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Abstract

The main aim of this paper is to select the best portfolio of renewable energy technologies (RETs) for electrifying an elected area which is not connected to any other grids. Minimizing total costs of the system is considered as the main factor in finding the best decision. In order to make the optimum plan more applicable, the technique of life cycle analysis is applied. This technique takes into account all costs of the system from the manufacturing stage of the different parts of a power plant until their disposal. Also, demand-side management alternatives are considered as competing solutions against the mentioned supply side options. To tackle the problem, an integrated and complex mathematical formulation is developed for finding the optimum energy plan regarding the real world assumptions. For the reason of NP-hard nature of the proposed model and that it is hard-to-solve for real large sized problems, a genetic algorithm (GA) approach is additionally developed for solving the medium and large size mixed integer non-linear models. To evaluate the performance of the proposed GA, a range of random test problems are conducted. The obtained results show that the length of planning period is the core factor in selecting the appropriate portfolio of RETs. Furthermore, it is shown that the proposed GA is capable of producing good results in almost negligible processing times.

Keywords: Life cycle assessment, demand side management; genetic algorithm, energy consumption

1- Introduction

Nowadays, due to the ongoing increase in consumption of energy, high rate of growth in consumption of electricity, and the recent increase in the price of the electricity, some policies are adopted by countries on energy consumption to control it. In the latest years, increase in energy efficiency by means of demand side management (DSM) is treated as a monumental step to success in

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energy management. Furthermore, from the economic point of view, considering power house's costs in their whole-life time and trying to invest in the least-expensive power plants is very essential.

Energy demands management, also known as DSM, aims to modify energy consumption patterns through several ways including financial motivations and training people. By doing these suggestions, need for installing new power plants can be deferred. This fact represents a new approach to plan at electric utilities. Generally, the goal of DSM is to reduce peak loads by shifting consumer patterns to utilize less energy through the peak times, or to transfer the time of energy utilization to off-peak times such as nighttime and weekends. Management of peak demand does not necessarily reduce the total energy consumption, but could be expected to decrease the need for the investments in networks and/or power plants. Energy demand management activities should take the demand and supply closer to a reachable optimum value. DSM is developed as a program or plan designed for energy consumption control with respect to customer needs. In this area, saving, energy efficiency, and load management can be addressed (Mullally2007). The proper use of DSM technologies could reduce the necessity of new installed intermittent power to achieve the renewable permeation goals (Moura, & de Almeida 2010).

DSM programs play an important role in energy generation projects. Pelzer et al. (2008) investigated effects of DSM in similar projects in a case study. They studied typical production and operating constraints such as safety constraints, maximum number of equipment activate daily, minimum and maximum storage/reservoir levels, and capacity limitation. Moura& de Almeida (2010) proposed a new multi-objective model to optimize the mix of renewable system, maximizing its contribution to the peak load at a minimum cost. However, the contribution of the large-scale DSM and demand response technologies was neglected and the current paper addresses it in the presented model.

In a recent study, Kazemi& Rabbani (2013) proposed an integrated Decentralized Energy Planning (DEP) model wherein DSM policies were capably regarded as a competitive solution against the supply-side alternatives for electrifying a rural area. Based on their obtained results, DSM policies were contributing to electrify the supposed area at their maximum capacity. DEP aims for efficient use of local resources to supply energy. A DEP for optimal allocation of resources in a rural area is developed in some researches. Devadas (2001) suggested a linear programming model that its objective function was maximization of revenue for the under study village with regard to energy and non-energy constraints. A DEP model for a rural area in Colombia where the energy requirements must be met from local sources was suggested by Herran&Nakata (2008). They used a multi objective function for integrated assessment of electrical power systems by renewable technologies. Hiremathet al. (2009) represented a multi objective optimization model of DEP for a village in India. They proposed Linear Programming (LP) models and the goal Programming (GP) methods were used for solving the problem. Iniyanet al. (1998) have suggested an optimal Renewable Energy model (OREM) for optimal allocation of renewable-energy sources to demand spots in different parts of India. Senjyuet al. (2007) used a genetic algorithm (GA) in finding a rational configuration of power generation systems in islands that want to establish renewable powerhouses.

Another essential criterion to make a sound energy plan is life cycle assessment (LCA). Generally, applying LCA is operational tool thinking in a quantitative way on environmental analysis of activities related to processes or products (goods or services). A central characteristic of LCA is the holistic focus on products or processes and their functions considering upstream and downstream activities. LCA of a productincludes all the production processes and services associated with the product through its life cycle, from the removal of raw materials through production of the materials which are used in the manufacturing of the product, over the use of the product, to its recycling and/or ultimate clearance of some of its components. Such a complete life cycle is also often named "cradle to grave." Hence, this life cycle of a product is identical to the complete supply chain of the product plus its use and the end-of-life treatment. During the past decade, an increasing number of papers have been published in LCA field, covering a variety of problems. Fayet al. (2000) investigated LCA in building cases. Changet al. (2010) assessed the energy and environmental impacts of civil construction in China with an input-output LCA model. Cooperet al. (2011) have stressed some critical aspects of LCA which are required to be considered in comparing different farming systems. Hertwich (2005) investigated life cycle approaches for sustainable consumption in a critical review and presented that the methods have many bugs and should be studied more in this topic. Góralczyk

(2003) claimed that LCA can be applied to evaluate the environmental impacts of electricity generation. The assessment aims to the environmental impact analysis to produce energy from energy sources such as photovoltaic (PV), wind and hydroelectric power. The paper covers the construction, operation and waste disposal at each power plant. Pehnt (2006) examines a dynamic approach towards the LCA of renewable-energy technologies. This approach is discussed for energies that consist of wind power, solar thermal, geothermal energy, PV, biomass and hydropower. Daniel Weisser (2007) investigated greenhouse-gas emissions of several technologies with LCA and compared them together. Bhat& Prakash (2009) reviewed the LCA for wind energy, solar PV, solar thermal, biomass and hydro power systems. Life time, power rating and emission for each system are collected and compared with conventional systems. Rodríguezet al. (2011) in a paper developed a new type of indicators that is based on energy life cycle data to answer which energy alternatives are better than others.

Decrease of fossil-fuel consumption in the energy sectors is a crucial step towards more sustainable energy production and is discussed in Tonini&Astrup (2012). Environmental impacts related to possible future energy systems with high shares of wind and biomass energy were evaluated using LCA. Some other studies considered researches are about LCA in one of renewable energy technologies such as wind (Martinezet al. 2009; Schleisner2000; Crawford 2009; Dismukes et al. (2009)), PV (Dones&Frischknecht(1998), Sherwani&Usmani 2010),geothermal (Fricket al. 2010) and biomass (Helleret al. 2004, Jorqueraet al. 2010).As it is depicted in previous researches, costs have been considered as average operational costs over the years in the energy generation field. Therefore; in this study, LCA applies to the total project costs in order to have a comprehensive investigation in the energy field with regard to weaknesses of the past researches in cost analyzing. These costs encompass all costs of system from the producing of the first part of powerhouse to its destroying time. Moreover, DSM alternatives are considered as competing solutions against supply side options for electrifying the area under the study. Finally, an integrated and complex mathematical formulation is developed to find the optimum energy plan with consideration ofthe model assumptions.

Since the proposed model is NP-hard problem, and it is hard-to-solve for real scale problems, a GA methodis developed in additionto solve the mixed integer non-linear model. The obtained results of the proposed metaheuristic are compared against the results of the GAMS optimization software for small test problems. It shows that the proposed method has a rational performance from both time and quality points of view.

The rest of the paper is organized as follows: In section 2, the proposed mathematical formulation is presented and an illustrative example is optimally solved using GAMS optimization software. Section 3 describes the devised and innovative GA to solve the proposed problem. Section 4 allocates to the experimental results obtained through the solving GA for both small-scale and large-scale test problems. Finally, in section 5, the conclusion remarks are drawn.

2- Problem Definition

2-1- Proposed model

In this section the proposed model which is based on the following assumptions is presented:

- Demand has a dynamic nature and the amount of demand can be different for years.
- Each powerhouse has a life time, and at the end of this time it is discarded from the cycle of demand supply.
- Combinations of powerhouses can be used in order to meet the demand of each year.
- Transferring energy between different areas is not permitted.
- Each powerhouse has different capacities and there are different initial investments cost, operation cost, and maintenance cost for each one. Furthermore, each of them has a different life time.
- A time-dependent annual rate of operation cost is considered.
- Operation cost of each powerhouse depends on the amount of electricity generated in the powerhouse.
- Maintenance costs of each powerhouse during its life time are assumed to be constant.
- DSM has a life time when a DSM is running, we cannot run another one until its life time is over.
- DSM program has establishment (IDSM) and operation costs (CDSM).

- DSM has upper bound in all parts and at all.
- If at the end of the fiftieth year the powerhouse's life time is not finished, the remaining value of powerhouse will be estimated and subtracted from its total cost.

The nomenclature used in this article is as follows:

Indices:

i : Renewable-energy technologies
j : End- uses
k : Types of renewable-energy technologies
t : Years

Parameters:

C_{ik}^{t} : Electricity generation cost of resource *i* type *k* in *t*th year ($US\ \$/kWh$)
$C_{ik}^{'t}$: Maintenance cost of resource *i* type *k* in *t*th year ($US\ \$$)
I_{ik}^{t} : Resource *i* type *k* implementation cost in year *t* ($US\ \$$)
$IDSM^{t}$: The initial cost of DSM program implementation in *t*th year ($US\ \$$)
$CDSM_{j}^{t}$: Electricity saving cost using the implemented DSM program in *j*th end-use in *t*th year ($US\ \$/kWh$)
CV_{ik}^{t} : Salvage revenue in year *t* subtracted from salvage cost of resource *i* type *k* ($US\ \$$)
t_{ik} : Life cycle of resource *i* type *k* (year)
t_{DSM} : Life cycle of resource *i* type *k* (year)
V_{ik} : The salvage value subtracted from initial value of resource *i* type *k* ($US\ \$$)
D^{t} : Total energy demand in *t*th year (kWh)
P_{j} : The maximum possible saving using the DSM program in the *j*th end-use in *t*th year (kWh)
Cap_{ik} : Total capacity of resource *i* type *k* in year *t* (kWh)

Decision variables:

X_{ik}^{t} : Optimal amount of used capacity of resource *i* type *k* in *t*th year (kWh)
$X_{ik}^{'t}$: Optimal amount of electricity generation of resource *i* type *k* in year *t* (kWh)

$$Y_{ik}^{t}=\begin{cases}1 & \text{if resource i type k is stablished in year t}\\ 0 & \text{o.w.}\end{cases}$$

$SDSM_{j}^{t}$: Optimal saving in *j*th end-use in *t*th year using the implemented DSM program (kWh)
$SDSM^{t}$: Total optimal saving in *t*th year using the implemented DSM program (kWh)

$$w^{t}=\begin{cases}1 & \text{if DSM program is implemented in year t}\\ 0 & \text{o.w.}\end{cases}$$

F_{ik}^{t} : Number of resource *i* type *k* in hand in year *t*
M_{ik}^{t} : The number of years that is resource *i* type *k* has been used (years)
B_{ik} : Maximum number of resource *i* type *k* establishment in each year.

The proposed model is formulated as follows:

Objective function:

$$Minimize\ \ NPV=\sum_{t=1}^{50}\sum_i\sum_k C_{ik}^{t}X_{ik}^{'t}(\frac{P}{F},i\%,t)+\sum_{t=1}^{50}\sum_i\sum_k C_{ik}^{t}F_{ik}^{t}(\frac{P}{F},i\%,t)$$

$$+\sum_{t=1}^{50}\sum_i\sum_k Y_{ik}^{t}X_{ik}^{t}I_{ik}^{t}(\frac{P}{F},i\%,t)+\sum_{t=1}^{50}w^{t}IDSM^{t}(\frac{P}{F},i\%,t)+\sum_{t=1}^{50}\sum_j CDSM_j^{t}SDSM_j^{t}(\frac{P}{F},i\%,t)$$

$$+\sum_{t=\min\{t_{ik}\}}^{50}\sum_i\sum_k Y_{ik}^{t-t_{ik}+1}cap_{ik}^{t-t_{ik}+1}CV_{ik}^{t}(\frac{P}{F},i\%,t)+\sum_{t=1}^{50}\sum_i\sum_k((t_{ik}-M_{ik}^{t})/t_{ik})\,X_{ik}^{t}V_{ik}^{t}(\frac{P}{F},i\%,t)\qquad(1)$$

Constraints:

$$\sum_i\sum_k X_{ik}^{t}Y_{ik}^{t}Cap_{ik}+SDSM^{t}w^{t}\prod_{b=t-t_{DSM}+1}^{t-1}(1-w^{b})$$

$$\geq D^{t}-\sum_i\sum_k\sum_{e=t-t_{ik}+1}^{t-1}(F_{ik}^{t-1}Cap_{ik})-SDSM^{t}w^{t}\qquad,\forall t\qquad(2)$$

$$SDSM^{t}\leq\sum_j SDSM_j^{t}\qquad,\forall t\qquad(3)$$

$$F_{ik}^{t}\leq\sum_{s=t-t_{ik}+1}^{t}Y_{ik}^{s}X_{ik}^{s}\qquad,\forall i,k,t\qquad(4)$$

$$\sum_i\sum_k X_{ik}^{'t}\geq D^{t}\qquad,\forall t\qquad(5)$$

$$X_{ik}^{'t}\leq Cap_{ik}F_{ik}^{t}\qquad,\forall i,k,t\qquad(6)$$

$$M_{ik}^{o}=(50-o)Y_{ik}^{o}\qquad,\forall i,k,o=50-t_{ik}+1,...,50\qquad(7)$$

$$SDSM_j^{t}\leq P_j\qquad,\forall j,t\qquad(8)$$

$$X_{ik}^{t}\leq 10Y_{ik}^{t}\qquad,\forall i,k,t\qquad(9)$$

$$X_{ik}^{t}\leq B_{ik}\qquad,\forall i,k,t\qquad(10)$$

$$Y_{ik}^{t},w^{t}\in\{0,1\}\qquad,\forall i,k,t\qquad(11)$$

$$F_{ik}^{t},\ X_{ik}^{t},\ M_{ik}^{t}\quad \text{Integer}\qquad,\forall i,k,t\qquad(12)$$

$$SDSM^{t},\ SDSM_j^{t},\ X_{ik}^{'t}\geq 0\qquad,\forall i,k,t\qquad(13)$$

The objective function minimizes total electricity generation costs for 50 years using the Net Present Value (NPV) method. This function consists of seven parts. Part one, will minimize operational costs in all years that are depended on the amount of electricity which is not generated. Term two, stands for maintenance costs in all years and independent on the amount of generated electricity whereas it is affected by the number of resources in year *t*.

Establishing cost of resources is stated in part three wherein all costs of investment and locating are defined. Terms four and five are related to DSM program that includes both primary and operational costs. Part six shows salvage cost of each resource with consideration of salvage revenue. This section can be a positive or negative number (depending on its salvage cost and revenue). Part seven of the objective function value is the remained value of resources at the end of our life cycle (50 years), and this part is subtracted from the objective function.

In part one up to six, the costs of all years are returned to the first year by P/F factor with a defined interest rate while in part seven the remaining value is returned from just the last year to the initial year.

Constraint (2) checks to supply the demand with regard to DSM planning. Each powerhouse has its predetermined life time and when each one is located, its life time must be considered. This point is done by subtracting the capacity of the allocated plants. Constraint (3) calculates the total optimal saving achieved in year *t* using the implemented DSM program (kWh). Constraint (4) calculates the number of resources *i* of type *k* which are available in year *t*. Constraint (5) denotes that amounted of generated electricity in year t must be greater than the demand of that year. Constraint (6) ensures that the optimal amount of electricity generation of resource *i* of type *k* in year *t* must be less than or equal to its capacity. Constraint (7) contributes to calculate the estimated residual values. Constraint (8) imposes an upper bound on DSM achievements. Constraint (9) relates variables *y* and *x* together, i.e. if *x* takes a number greater than zero, then y must be 1. Lastly, the 10th constraint limits the number of facilities located.

3 - Illustrative example

In this subsection, a test problem with two energy technology is considered.Each technology has two different types for four end-uses. Time duration is supposed 25 years and this modelis solved with GAMS 23.2 software. The data related to this problem are shown in the Tables 1-11 are utilized for validation of the proposed model. By supposing this data, Table 12 shows GAMS results in small size.

$i = \{1,2\}$, $k = \{1,2\}$, $j = \{1,...,4\}$, $t = \{1,2,...,25\}$ and $t_{DSM} = 10$

Table1. Maximum possible saving using DSM

j	1	2	3	4
P_j	1000	200	2000	300

Table2. Electricity generation costs.

C_{ik}^t	i	k	Time Periods 1	2	3	4	5	6	7	8	9	10	11	12	13
	1	1	88.5	95.6	103.2	111.5	120.4	130.0	140.4	151.7	163.8	176.9	191.1	206.4	229.0
	1	2	63.0	68.0	73.5	79.4	85.7	92.6	100.0	108.0	116.6	125.9	136.0	146.9	163.1
	2	1	34.2	37.6	41.3	45.5	50.0	55.0	60.5	66.6	73.2	80.6	88.6	97.5	107.2
	2	2	34.2	37.6	41.3	45.5	50.0	55.0	60.5	66.6	73.2	80.6	88.6	97.5	107.2

i	k	Time Periods 14	15	16	17	18	19	20	21	22	23	24	25
1	1	254.2	282.2	313.3	347.7	386.0	428.4	475.5	527.9	585.9	650.4	721.9	801.3
1	2	181.0	200.9	223.0	247.5	274.8	305.0	338.5	375.8	417.1	463.0	513.9	570.4
2	1	117.9	129.7	142.7	157.0	172.7	189.9	208.9	229.8	252.8	278.1	305.9	336.5
2	2	117.9	129.7	142.7	157.0	172.7	189.9	208.9	229.8	252.8	278.1	305.9	336.5

Table 3. Maintenance costs.

			Time Periods												
C'^{t}_{ik}	i	k	1	2	3	4	5	6	7	8	9	10	11	12	13
	1	1	28.5	35.6	43.2	51.5	60.4	70.0	80.4	91.7	103.8	116.9	131.1	146.4	169.0
	1	2	38.0	43.0	48.5	54.4	60.7	67.6	75.0	83.0	91.6	100.9	111.0	121.9	138.1
	2	1	64.2	67.6	71.3	75.5	80.0	85.0	90.5	96.6	103.2	110.6	118.6	127.5	137.2
	2	2	79.2	82.6	86.3	90.5	95.0	100.0	105.5	111.6	118.2	125.6	133.6	142.5	152.2

		Time Periods											
i	k	14	15	16	17	18	19	20	21	22	23	24	25
1	1	194.2	222.2	253.3	287.7	326.0	368.4	415.5	467.9	525.9	590.4	661.9	741.3
1	2	156.0	175.9	198.0	222.5	249.8	280.0	313.5	350.8	392.1	438.0	488.9	545.4
2	1	147.9	159.7	172.7	187.0	202.7	219.9	238.9	259.8	282.8	308.1	335.9	366.5
2	2	162.9	174.7	187.7	202.0	217.7	234.9	253.9	274.8	297.8	323.1	350.9	381.5

Table 4. Salvage revenue subtracted from initial value of resource.

CV_{ik}^{t}	i	k	Time Periods 1	2	3	4	5	6	7	8	9	10	11	12	13
	1	1	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000
	1	2	120000	120000	120000	120000	120000	120000	120000	120000	120000	120000	120000	120000	120000
	2	1	140000	140000	140000	140000	140000	140000	140000	140000	140000	140000	140000	140000	140000
	2	2	170000	170000	170000	170000	170000	170000	170000	170000	170000	170000	170000	170000	170000

i	k	Time Periods 14	15	16	17	18	19	20	21	22	23	24	25
1	1	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000	100000
1	2	120000	120000	120000	120000	120000	120000	120000	120000	120000	120000	120000	120000
2	1	140000	140000	140000	140000	140000	140000	140000	140000	140000	140000	140000	140000
2	2	170000	170000	170000	170000	170000	170000	170000	170000	170000	170000	170000	170000

Table 5. Implementation costs.

I_{ik}^{t}	i	k	Time Periods 1	2	3	4	5	6	7	8	9	10	11	12	13
	1	1	860000	865000	870000	875000	880000	885000	890000	895000	900000	905000	910000	915000	920000
	1	2	2800000	2805000	2810000	2815000	2820000	2825000	2830000	2835000	2840000	2845000	2850000	2855000	2860000
	2	1	1500000	1505000	1510000	1515000	1520000	1525000	1530000	1535000	1540000	1545000	1550000	1555000	1560000
	2	2	3200000	3270000	3340000	3410000	3480000	3550000	3620000	3690000	3760000	3830000	3900000	3970000	4040000

i	k	Time Periods 14	15	16	17	18	19	20	21	22	23	24	25
1	1	910000	900000	890000	880000	870000	860000	850000	840000	830000	820000	810000	800000
1	2	2865000	2870000	2875000	2880000	2885000	2890000	2895000	2900000	2905000	2910000	2915000	2920000
2	1	1565000	1570000	1575000	1580000	1585000	1590000	1595000	1600000	1605000	1610000	1615000	1620000
2	2	4110000	4180000	4250000	4320000	4390000	4460000	4530000	4600000	4670000	4740000	4810000	4880000

Table 6. Life time of resources.

t_{ik}	i \ k	1	2
	1	25	25
	2	25	25

Table 7. Capacity of resources.

Cap_{ik}	i \ k	1	2
	1	180000	360000
	2	150000	480000

Table 8. Salvage value.

V_{ik}	i \ k	1	2
	1	221000	609000
	2	249000	1326000

Table 9. Electricity demand.

D^t	1	2	3	4	5	6	7	8	9	10	11	12	13
	2000000	2050000	2100000	2150000	2200000	2250000	2300000	2350000	2400000	2450000	2500000	2550000	2600000
	14	15	16	17	18	19	20	21	22	23	24	25	
	2650000	2700000	2750000	2800000	2850000	2900000	2950000	3000000	3050000	3100000	3150000	3200000	

Table 10. DSM implementation cost.

$IDSM^t$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900	6900

Table 11. DSM cost over time.

$CDSM_j^t$	Time Periods												
j	1	2	3	4	5	6	7	8	9	10	11	12	13
1	40	40	40	40	40	40	40	40	40	40	40	40	40
2	20	20	20	20	20	20	20	20	20	20	20	20	20
3	30	30	30	30	30	30	30	30	30	30	30	30	30
4	5	5	5	5	5	5	5	5	5	5	5	5	5

	Time Periods											
j	14	15	16	17	18	19	20	21	22	23	24	25
1	40	40	40	40	40	40	40	40	40	40	40	40
2	20	20	20	20	20	20	20	20	20	20	20	20
3	30	30	30	30	30	30	30	30	30	30	30	30
4	5	5	5	5	5	5	5	5	5	5	5	5

Table 12. GAMS results (Small size)

NO.	Problems			CPU times (second)	Objective function values
	Number of facilities/kind		Time periods		
example	GAMS	4/solar=2 , wind=2	25	5592s	1.62534×e9

The aim of illustrating this example is twofold. First, the model is mathematically validated and its feasibility is proven. Secondly, it is indicated that the model is really complex and very time consuming even for such a small test problem. In this case which has only two energy technologies, two different capacities for each technology and 25 years as total number of periods, it takes nearly 2 hours CPU time to find the optimum solution using GAMS optimization solver.One way to accomplish this task in shorter running time is to use of metaheuristic algorithms. The most salient feature of these algorithms that have made them popular among researchers and practitioners is their abilities at providing well-qualified solutions in a very short period of time. A well-known metaheuristic algorithm is GA that tries to find global optimum solution through an evolutionary mechanism. Since, this method is very easy to apply and also very efficient in almost every optimization problems, it is chosen to solve the proposed model for this article. The way that this method is applied for the proposed model is completely discussed in the next section.

4- Solution methodology

Recently, GAs have received considerable attention to be used as an optimization technique to solve the problems in so many fields of science. GA is an intelligent probabilistic search algorithm that works by preserving and adapting the characteristics of a set of trial solutions (*npop*) over a number of iterations (*maxit*). Each individual solution is represented by a string which is referred to as chromosome and includes a set of random numbers called genes. GA is capable of retaining desirable characteristics that may be ignored by completely random searches, and this is a good property for an optimization algorithm. Interested readers about the methodology of GA can refer to Rabbani et al. (2016). GA has three general steps as follows:

(1) Generate initial population. (Chromosomes of first population)
(2) Calculate fitness function of each chromosome.
(3) New population generation.

Each chromosome includes genes that are binary matrix and these matrices show which facilities are located. There are several ways to code all the stages of GA. The applied GA in this paper is described in next sections.

4-1- Initialization

In this problem, the population size is set to be 100. Initially, a random integer matrix that each cell stands for the number of powerhouse typei' or $SDSM_j$ in period $t$is generated for the first population, and then we utilize a calculating function on each chromosome of the initial population. We have three indices, so primary matrix is three-dimensional matrix, but for convenience, indices i and $k$combined together as follows (Table 13):

Table13. Dimension coding

i	k	i'
1	1	1
1	2	2
1	3	3
2	1	4
2	2	5
2	3	6

With these new coded indices all of our three-dimensional matrices have been converted to two-dimensional matrices. Therefore, we can show number of powerhouse kind i' established in period t ($x_{i'}^{\prime t}$), with the upper part of the following matrix which is shown in Fig 1:

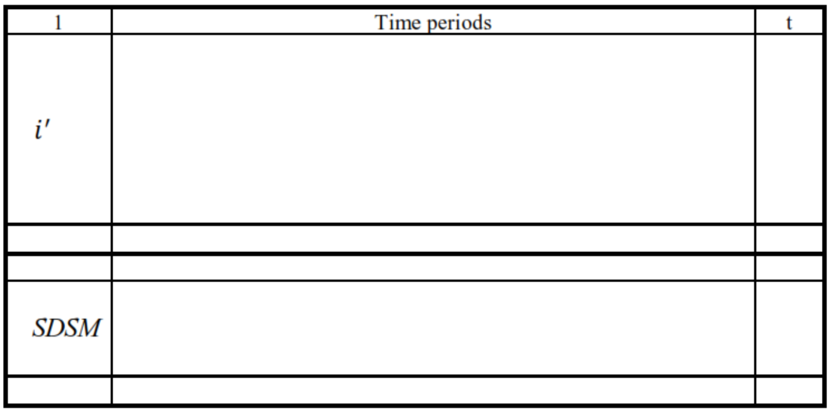

Fig. 1: The structure of first part of chromosome

The lower part of this matrix showsthe amount of SDSMs in each periods.Given the matrix above as an encoded feasible solution, a one-to-one relation between the solution space and the new encoded space can be established. By having this matrix and using a sign function on the first part of the matrix, the value of variable Y can be calculated. Subsequently, variables x, F, and w can also be calculated and thus the fitness of each solution is gained.

4-2- Fitness function and penalty strategy

After all of those evaluations, the fitness function is calculated for the population. According to the objective function, the mathematical evaluation wrote in MATLAB software. All chromosomes should fallow up this terms; first, supplying energy demand in every period, second, confirming that we cannot run DSM program in life cycle of another before. For fitness function of any chromosome that cannot supply these terms, a specific penalty policy is considered.In each period, it is consideredthat if its demand is not supplied, it will charge 1,000,000$ cost penalty and each demand side management that began in other DSM life time will charge 2,000,000$ cost penalty.

4-3- Crossover operator

For parent selection, tournament method is selected. In this method, specific number chromosomes are selected randomly and the best chromosome is the tournament winner.

Two crossover operators are applied randomly for the optimization. First one is column two points; second one is row one point, one time for powerhouse and another one for SDSMs (Fig 2). These are formal crossovers, but for earlier convergence the local search is decided to run.

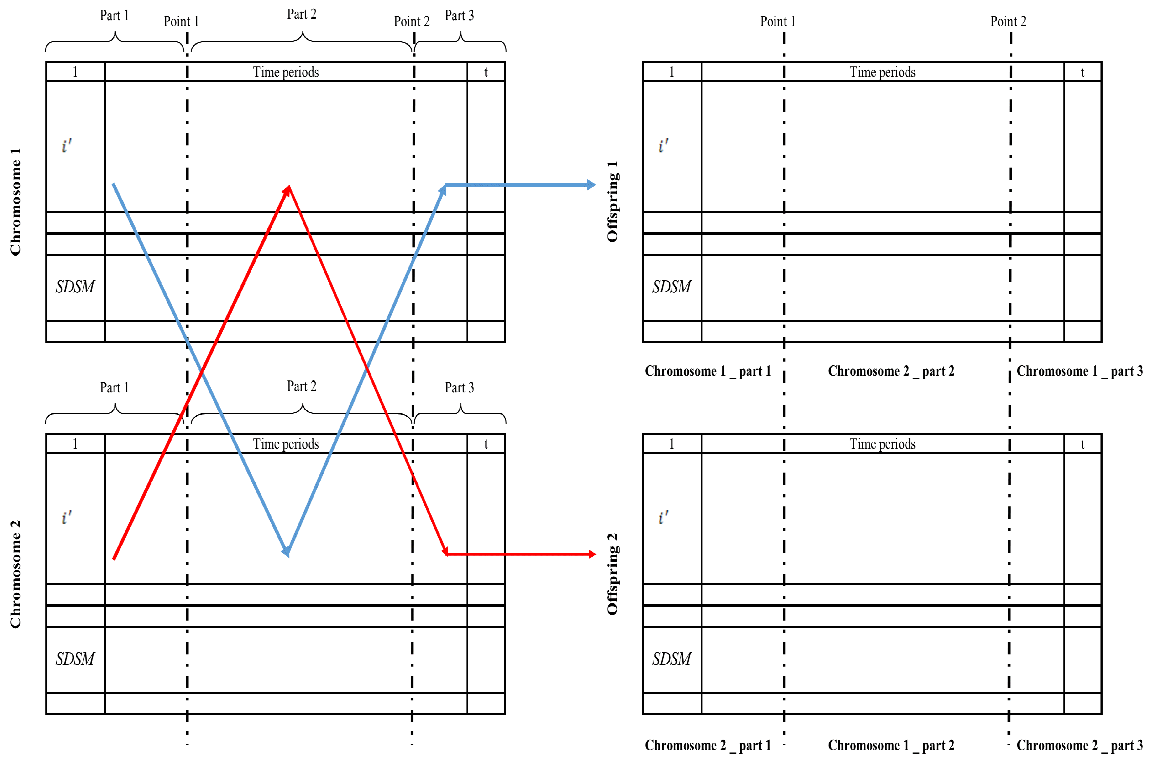

Fig. 2: Method of creating crossovers

4-4- Mutation

Two different mutation operators are applied for the GA used to optimize the problem. The first one changes randomly in the first period of matrix (Fig 3); the second one changes in some of cells except the first period of chromosomes (Fig 4). Number of mutations in is equal with *rate of mutation* (Mu) × *number of cells* in every chromosome.

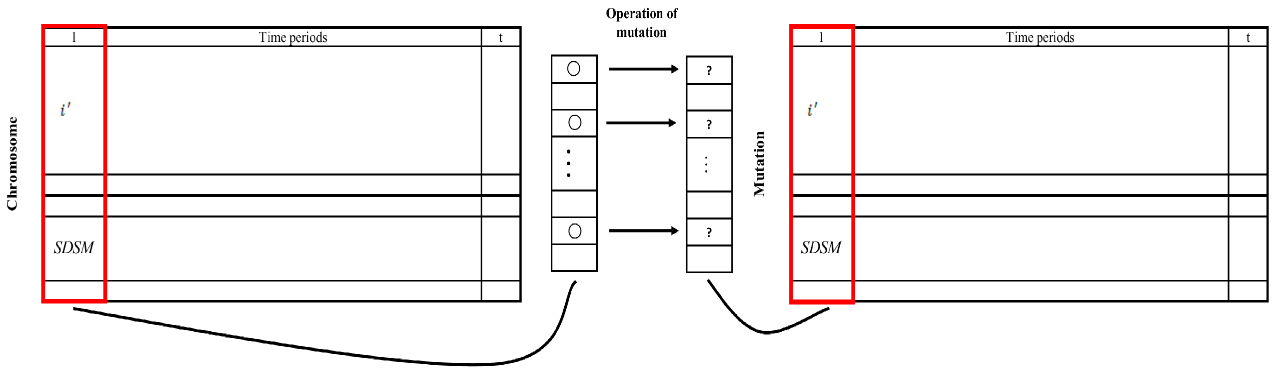

Fig. 3: First method for creating mutation

4-5- Local search

Two different local search functions are applied. In the first one, some chromosomes are selected, then with a random function we subtract 1 or 2 or sum 1 with chosen sells (Fig 5). In the second function, we calculate sum of generating potential of setting up powerhouses and then if this sum was more than demand of that period, we reduce the number of powerhouses in that period (Fig 6). In the first local search, we look for a chromosome that is very close to the original chromosome but we hope of some change, the fitness function become well. In the second local search, we hope to reduce the cost with decreasing the number of powerhouses set up in every period.

```
Local search No.1

a= three integer random numbers between 1 and number of chromosome row;
b= ten integer random numbers between 1 and number of chromosome column;

        A for loop with i=1 until i=3
                A for loop with j=1 until j=10
                        c=an integer random number between 1 and 3;
                        If c=1 then reduce amount 1 form sell ( i,j);
                        If c=2 then reduce amount 2 from sell ( i,j);
                        If c=3 then add amount 1 to sell ( i,j);
                End of second loop
        End of first loop
End of local search
```

Fig. 5: Local search No.1 algorithm

```
Local search No.2

A for loop with i=1 until i=number of time period
        s (i)= max amount of electricity generating for the chromosome in period t
End of loop
Count =0;
A while loop : count=0
        b= an integer random number between 1 and number of time period
        If demand of (b) < s(i)
                Find a cell bigger than of zero and reduce 1;
                Count=1;
End while
End of local search
```

Fig. 6: Local search No.2 algorithm

4-6- Replacement strategy

The elitist strategy is applied in this problem. In each iteration the best chromosome selected as one of the chromosomes in the next population, in addition to the chromosomes (parents and off springs) which are ranked after cross over and mutation according to their objective values. Among these ranked chromosomes, 100 of the best chromosomes are selected as the next population.

5- Experimental results

This section is mainly focused on indicating how well the proposed genetic algorithm performs. To do so, a small size problem is firstly solved by both GAMS software and GA, and then the obtained results are compared. Afterward, through setting up nine different problems of different size the performance of GA is shown for problems of larger sizes. The outcomes have been demonstrated in Tables 14 and 15.

Table14: GAMS&GA results (Small size)

NO.	Problems			CPUtimes (second)	Objectivefunctionvalues
	Numberoffacilities/kind		Timeperiods		
comparing	GAMS	4/solar=2, wind=2	25	5592s	1.62534×e9
	GA	4/solar=2, wind=2	25	3984s	Gap : 7.53%
1	GA	4/solar=2, wind=2	First 30 years	4691s	2.43916×e9
			Other 20 years	2398s	1.84921×e9
2	GA	4/solar=2,wind=2	First 40 years	5356s	3.37743×e9
			Other 10 years	1263s	1.00418×e9
3	GA	4/solar=2, wind=2	50	6108s	4.17179×e9

Table15: GA results (Large size)

NO.	Problems		CPUtimes (second)	Objectivefunctionvalues
	Numberoffacilities/kind	Timeperiods		
4	6/solar=2, wind=2, hybrid=1, geo=1	First 30 years	6048s	2.51914×e9
		Other 20 years	4309s	1.89132×e9
5	6/solar=2,wind=2, hybrid=1, geo=1	First 40 years	6652s	3.45474×e9
		Other 10 years	2201s	1.10429×e9
6	6/solar=2, wind=2, hybrid=1, geo=1	50	7689s	4.27527×e9
7	8/solar=3, wind=2, hybrid=2, geo=1	First 30 years	8114s	2.31347×e9
		Other 20 years	5319s	1.95721×e9
8	8/solar=3, wind=2, hybrid=2, geo=1	First 40 years	8513s	3.09975×e9
		Other 10 years	3914s	1.24781×e9
9	8/solar=3, wind=2,hybrid=2, geo=1	50	10449s	4.06216×e9

As it can be seen from Tables 14 and 15, the total number of periods has been considered to be 50 years, while 9 different problems and 3 scenarios are investigated. In the first scenario, the energy supply plan was initially determined for the first 30 years and then for the next 20 years; in the second scenario, the energy plan of the first 40 years was established at the outset and after that the next 10 years' energy plan was investigated. At last, in the third scenario, all the 50 years was taken into account altogether. The obtained results indicate that when the time period is considered as one big period of time, the outcomes are more effective and practical than those obtained when the whole period of time is divided into small bucket periods.

This superiority for big bucket plans is not only related to achieving cost-effective plans but also contributes to reaching shorter CPU times for solving the problems. Therefore, it can be concluded that life cycle analysis is a crucial tool for making energy planning decisions.

Moreover, it can be deduced that the length of planning period is a key factor in selecting the appropriate type of energy resource technology. For instance, for time periods less than 35 years, the use of hydro power plants is not recommended. It is mostly due to the fact that the usual life cycle of a typical hydro power plant is about 50 years and thus for planning periods shorter than 50 years hydro power plants are not a cost-effective solution.

6- Conclusions and future directions

The main aim of this paper was to select the best portfolio of renewable energy technologies (RETs) for electrifying a secluded area. Minimizing total costs of the system was considered as the key feature in finding the optimum decision. In order to make the optimum plan more realized, the technique of life cycle analysis was applied. To cope with the problem a nonlinear mixed integer programming formulation was developed. Also, a genetic algorithm was proposed to solve the formulation for large scale test problems. Afterward a variety of test problems in three different scenarios was considered. The obtained results indicated that when the time period is considered as one big period of time, the outcomes are more effective and practical than those obtained when the whole period of time is divided into small bucket periods. This superiority for big bucket plans is not only related to achieving cost-effective plans, but also contributes to reaching shorter CPU times for solving the problems. Therefore, it is concluded that life cycle analysis is a crucial tool for making energy planning decisions.Moreover, it was shown that the length of planning period is a key factor in selecting the appropriate type of energy resource technology. For instance, for time periods less than 35 years, the use of hydro power plants is not recommended. It is mostly due to the fact that the usual life cycle of a typical hydro power plant is about 50 years and thus for planning periods shorter than 50 years hydro power plants are not a cost-effective solution.

For future study, the respected researchers are advised to add environmental factors to the decision criteria and reformulate the model accordingly. Also, skillful human resource availability should be investigated in such secluded areas.

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