Determination of Biomass Power Plant Location Using GIS-Based Heuristic Methods: A Case Study in Turkey

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Research Article

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Posted Date: January 14th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-953284/v1

Determination of biomass power plant location using GIS based heuristic methods: A case study in Turkey

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Abstract

Biomass conversion to bioenergy has always been necessary to ensure the most efficient use of the limited biomass resource and enable economic viability. Evaluating biomass transportation cost, electricity transmission cost and heat transferring cost between power plant location/s and supply/demand points and selection of an optimum power plant capacity is an important issue for a robust supply chain design. In this study, we employed designing optimum biomass to the bioenergy supply chain for agricultural activities using Geographic Information System and Simulated Annealing algorithm to overcome a real-world problem in Bismil District of Diyarbakır/Turkey. Our goal is to define a potential investment location/s on the trigeneration system by comparing the trade-offs between the raw material/end-product transportation costs and facility/s and pipeline installation costs. To determine possible locations for power plants, distance matrices were retrieved from suitable candidate power plant locations and agricultural parcel, settlement and the nearest high voltage electricity line from the Geographic Information System. The results showed that establishing one power plant is feasible. The net present value of a potential investment is almost 260 million Euros and the re-payment period is 1.33 years.

Keywords: Biomass Energy, Supply Chain Optimization, Facility Location Problem, Tri-generation, Simulated Annealing.

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1. Introduction

Biomass can be defined as the total mass of living organisms that belong to a society consists of species or consist of several species. Biomass is the most widely used renewable energy source in the world today. It is contributing to energy used in power generation, generating electricity, heating homes, fueling vehicles, heat for industry and buildings, and transport (IEA 2017). Today, the key notion in biomass utilization is excluding the traditional use of biomass. Biomass is commonly converted to energy through traditional methods that lead to inefficiency, health problems, and environmental pollution (Akgül and Seçkiner 2019). Efficiency varies from 5% to 15% in traditional methods; however, it reaches up to 90% in modern bioenergy facilities. Modern bioenergy term is generally used to refer to heat or electricity or transport biofuels and exclude the traditional use of biomass.

According to a report published by International Energy Agency (IEA 2017), Global biofuel production increased 10 billion liters in 2018 to reach a record 154 billion liters. Double the growth of 2017, this 7% year-on-year increase was the highest in five years. Output is forecast to increase 25% to 2024, an upwards revision from 2018 owing to better market prospects in Brazil, the United States and especially China. The goal for the year 2060 is 17%. Modern and traditional biomass accounts for 70% of all renewable energy production and nearly equivalent to that of coal in terms of final energy consumption. Electricity generated in bioenergy power plants accounts for 2% of the total electricity production and % 8 of renewable resource-based electricity production in the world in 2016. It is projected that biomass utilization will contribute to providing 20% carbon saving up to 2060. The total biomass energy potential of Turkey is about 33 million tons of oil equivalents (Mtoe). The amount of usable biomass potential of Turkey is approximately 17 Mtoe. The electrical production potential from usable bioenergy sources is 73 MW in 2010 and corporate income and represents more than 280,000 jobs (Toklu 2017). The traditional use of biomass is undesirable for both economic and environmental reasons. Governments across the world encourage the private sector to produce electricity from renewable energy resources. Turkey is one of these states, which has incentive tools with regards to renewable resource utilization. According to renewable energy law enacted in 2005, electricity generation from biomass and solar power has the highest price (13.3 USD Cent/kWh) guaranteed by the government. That price can reach up 18,1 USD Cent/kWh in case of utilizing national machines or equipment in power plants. However, the price of electricity generated from wind and geothermal power are 7.3 and 10.5 USD Cent/kWh, respectively. This indicates that energy production from biomass is the most valuable compared to other renewable energy resources.

Bioenergy accounts for 1.5% of renewable-based electricity production including hydropower in Turkey. This share is 0.7% when considering all kinds of electricity generation (General Directorate of Energy Affairs 2018). As might be seen from the figures, Turkey is below the world average in terms of bioenergy utilization. Given the limited natural energy reserves and extensiveness of agricultural lands of the country, the share of bioenergy is relatively low. The government has noticed this situation and set the goals to increase biomass utilization in modern conversion plants. Installed power of 1000 MW is targeted in biomass-based electricity generation in National Renewable Energy Action Plan. Biomass exploitation has crucial importance to reach this goal.

Biomass exploitation in modern conversion plants has increased in recent years. What drives this improvement are summarized as follows:

- Biomass can secure access to reliable energy resources,
- Carbon-neutrality is one of the major advantages of biomass energy
- Biomass utilization can make possible to earn more income for people living in rural areas,
- Bioenergy can be stored in liquid and gas form as an end or by-product,
- Biomass is a sustainable energy resource unlike fossil fuels
- Generating energy from biomass materials can greatly help in waste management
- Biomass energy is estimated to have a huge potential due to the abundant availability of biomass sources

Apart from the advantages, there are still some disadvantages to biomass exploitation in modern energy conversion plants. They are summarized as follows:

- Biomass contains carbon and it releases carbon dioxide on combustion and the time to recapture the carbon involved in biomass may vary depending on the type of biomass.
- Uncertainties in quantity,
- Unavailability in a given period (seasonal fluctuation),
- The construction and operating costs of a biomass energy plant can be expensive concerning traditional forms of power generation.
- Storage facilities require huge space, as harnessing energy from biomass involves a selection of different processes.
- High collection cost due to its geographically scattered structure,

Governments have some incentive tools to increase biomass utilization in modern facilities. Decrease of external dependence in energy supply and carbon emission is targeted thanks to

these incentives by governments. The high unit installation cost of bioenergy facility compared to fossil fuel-based facility is compensated with these subventions. Despite the incentives, biomass' geographically scattered structure, high transportation cost, seasonal fluctuation and uncertainty in quantity may make a potential investment infeasible at first glance. The collection and transportation cost of biomass accounts for 33-50% of the total biomass-to-bioenergy supply chain cost (Kumar et al. 2006) Drawbacks in the biomass-to-bioenergy supply chain can be eliminated through the scientific approach. Spatial analysis tools and optimization technics are convenient methods for designing a robust energy supply chain.

The remainder of this paper is organized as follows. Section 2 presents a literature review about other works closely related to the biomass to bio-energy supply chain problems which are solved through meta-heuristic methods. In section 3, heuristic method, problem description and geographic information system and spatial analysis tools for the problem dealt with are presented in materials and methods section. The real-world problem is addressed in Section 4 to illustrate the performance of the proposed heuristic technic. Finally, we conclude the paper and indicate future research directions in Section 5.

2. Literature review on biomass-to-bioenergy supply chain management

Bioenergy is derived from biomass which is a carbon-based biological material. Biomass is converted into energy via three main methods (Turkenburg 2000). Thermochemical, biochemical and extraction. Biochemical conversion is generally suitable for biomass which has a moisture content higher than 60% like livestock residues and wastewaters, while thermochemical methods are suitable for the biomass whose organic dry matter is higher than 60% like lignocellulosic material (Ciria et al. 2016). Lignocellulosic biomass, which is mainly composed of celluloses and lignin, is mostly derived from agricultural and forest activities. Corn and cotton are considered as a raw material in this study are an instance of lignocellulosic biomass.

Gasification, which is a thermochemical method, is considered as the biomass to gas conversion process since it is a suitable technology for lignocellulosic biomass. At the end of this process, syngas is produced which has a high calorific value and mainly composed of hydrogen, carbon monoxide, water, and fewer undesired contaminants. The syngas can run through gas turbines or other power conversion technology (prime mover) to produce electricity. Integrating some auxiliary equipment to prime mover allows generating cooling, heating, and power simultaneously. This is called trigeneration (combined cooling, heating, and power (CCHP)). In a trigeneration system, total system efficiency can reach up to 85% at full load, almost 40% of

which is accounted for electric efficiency, remaining is the thermal efficiency (Akgül and Seçkiner 2019). The load level affects the efficiency of prime mover positively. The district heating and cooling system (DHCS) must be integrated into a trigeneration system to transfer hot and cold heat demand points. Some parameters including pipe diameter, the distance between heat station and demand points, the temperature difference between supply and return water, pressure loss, outdoor temperature have an impact on heat losses. Trade-offs between these parameters must be analyzed to minimize heat loss.

The biomass supply chain comprises nine main consecutive steps: Cultivation, harvesting, loading, raw material transportation, unloading, warehousing, pretreatment, conversion to energy and end-product transportation. The baling and shredding (size reduction) sub-processes can be included to supply chain according to a given case. All processes except for cultivation, harvesting, loading, raw material transportation can take place in a trigeneration system. Minimizing any kind of losses between these successive processes calls for optimization technics.

Decisions on biomass to energy supply chain have been dealt with strategic, tactic and operational levels. The strategic level includes long-term decisions like the selection of site, capacity, technology, transportation node, biomass suppliers, and preprocessing facilities. Once a strategic decision is made, it is very unlikely to be altered in the short term (Yue and You 2016). Geographic Information Systems (GIS) has effective tools for all three levels, particularly at the strategic level.

Within the concert of renewable energy technologies, bioenergy can play a decisive role during the next decades, when smartly designed and applied under favorable conditions. In this respect, an efficient and effective supply chain and logistics management represents one key parameter (Turkenburg 2000). Efficient supply chain management and optimization is a very complex problem. To solve the sustainable biomass supply chain management problem, mathematical optimization modeling, heuristic or meta-heuristic solution technics can be analyzed with understanding the concept of biomass to bioenergy routes.

3. Materials and methods

3.1. Heuristic method

Unlike mathematical modeling, heuristic or meta-heuristics do not guarantee a globally optimal solution, however, they are very fast in complex problems such as NP-hard and NP-complete problems. They can optimize problems with non-linear, non-convex and non-continuous functions in a reasonable amount of time. Also, meta-heuristics, which are generally inspired by natural and physical events, is known as the most sophisticated heuristics. A heuristic is specific to the problem, while meta-heuristic can be applied to all kinds of problems. Heuristics may stick in local optimums and cannot be used in various types of problems, whereas meta-heuristic has ways out of local optimums and can be used in a wide range of problems (Ghaderi et al. 2016). As the size of the problem increases in combinational problems, the computational time of finding good or best solutions increases exponentially as well. Meta-heuristic algorithms can find near-optimum solutions for complex and large-scale problems in a short time.

Celli et al. (2008) used a GIS-based genetic algorithm to determine the number, capacity, and location of biogas facilities and applied the algorithm to a region in Italy. The objective function in the model is maximizing the profitability of the investment. Sultana and Kumar (2012) presented a location-allocation model embedded in GIS and applied it to a region in Canada. They used the Analytic Hierarchy Process (AHP) technic to identify the weight of predefined criteria for the selection of a pellet plant. After determining the number of candidate sites, the p-median solver method was employed in GIS to minimize the total biomass transportation cost. Reche-Lopez et al. (2009) used four meta-heuristics to determine the optimal placement and supply area of power plants and then compared solutions. All meta-heuristics were applied with experimental data. The profitability index was considered as the objective function. GIS was employed to divide the region into parcels with a constant surface of 2 km^2 and to provide the required data for optimization parameters. Rentizelas et al. (2009) modeled the bioenergy supply chain wherein the trigeneration system and district heating and cooling system were employed to make use of energy with an efficiency of almost 90%. The model was applied to a region in Greece to demonstrate its inherent capabilities. They considered five biomass types as feedstock (3 herbaceous and 2 woody out of which) and a single power plant to maximize the net present value of the potential investment by determining the optimal size, location, types and amounts of biomass to be used in a power plant. Vera et al. (2010) proposed a Binary Honey Bee Foraging algorithm that determines the capacity, location and supply area of biomass power plants. The objective function was formulated as maximization of investment profitability. The whole terrain

was divided into square-shaped cells in GIS. The centroids of each cell were identified as a candidate plant site.

In this study, as a solution technic, the simulated annealing algorithm was applied to biomass to bioenergy and reviewed in the literature survey. Especially, GIS based heuristic studies were examined and employed together with metaheuristic solution technics in some studies to simulate the actual case in a better way. GIS was also used exclusively as a site selection tool to determine suitable locations, particularly in waste management. However, these studies which are not integrated with heuristic algorithms such as SA were not addressed in the literature review. To the best of our knowledge, This is the first study on determination of biomass power plant location using GIS based-simulated annealing algorithm.

3.2. Problem definition

The general framework of this problem is different from our published study (Akgül and Seçkiner 2019). In this study, GIS tools were employed exactly to show the actual case and used a heuristic instead of mathematical modeling. Figure 1 demonstrates a schematic design of a bioenergy supply chain.

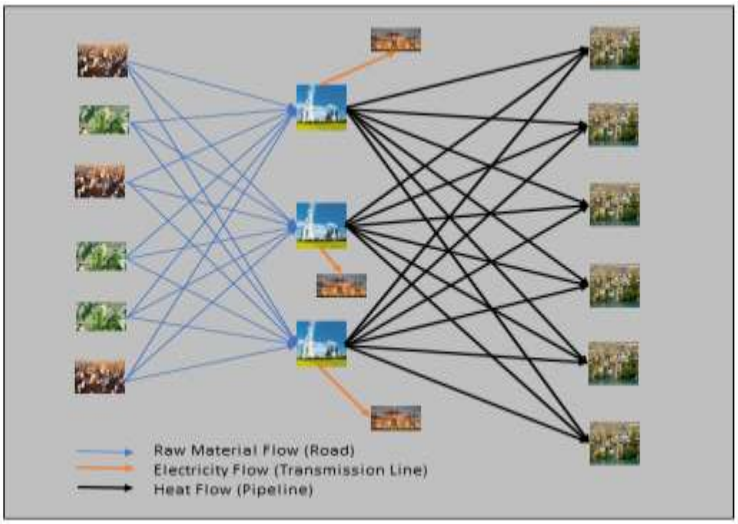

Figure1. A basic illustration of biomass to bioenergy supply chain [2]

3.3. Geographic information system (Spatial analysis)

In this section, a suitability model that was developed for the biomass to bioenergy supply chain design was introduced. This section aims to propose a model in a GIS environment for a selection of the most suitable candidate lands that were suited to a power plant building. The

selection process was carried out according to some preference criteria. ArcGIS software was employed for suitability analysis. The suitability model was applied to Bismil District in Diyarbakır Turkey.

Sitting a bioenergy facility in both the most suitable land and optimum location has crucial importance in the bioenergy sector. Selecting the most suitable land according to a set of particular criteria may reduce initial investment and operation costs. At the same time, it may boost annual revenues. In this regard, GIS is a powerful tool for determining the optimum location and selecting the most suitable lands. GIS is defined as collecting, storing, transforming, analyzing and visualizing spatial data obtained from the real world for a certain purpose employing some software tools and methods. Information systems built for the analysis of spatial data provide great convenience to policymakers in decision-making processes for the solution of complex social, economic and environmental problems experienced by human beings, as well as saving time, money and personnel (Goodchild 1997). The major components of the GISs are hardware, software, personnel, geographic data, and methods.

The GIS allows carrying out an advanced analysis like network and suitability analysis by using the topological properties of objects in the real world. To put it simply, traditional maps get smart thanks to GIS. GIS is capable of finding the optimal solution of location-allocation problems utilizing network analysis tools. Optimal size and location may be found by the utilization of network analysis tools depending on the size and type of the problem. However, our problem is highly complex. Thus, location-allocation analysis embedded in GIS could not be utilized. Instead, a meta-heuristic model was used to determine the optimum number, size, and locations of the power plant(s) and it's/their demand point/s (settlement) for providing heat. For this purpose, a meta-heuristic-based algorithm programmed in Excel Visual Basic Applications (VBA) was proposed. Real data, which was used in the proposed algorithm, was obtained through suitability analysis carried out in GIS.

As aforementioned, the proposed model was applied to Bismil District, Diyarbakır (Turkey) as a case study. Agricultural activities are very common in Bismil. A surface area of 1.737 km^2 is devoted to agriculture and 60% of which is irritable. According to a published study (Alibaş, et al. 2015), Bismil ranks first in herbal production among the other districts of Diyarbakır. Wheat, barley, lentil, cotton, and corn are cultivated in the agricultural land of Bismil. Cotton and corn are generally grown in irrigable areas (on the south part), while grain crops are grown in dry areas (on the north side). Agricultural parcels and candidate power plant locations were represented as a polygon, centroid coordinates of these polygons were represented as point and

distance matrixes were represented as a line in GIS. Vector data and raster data types were used in the proposed model.

The centroid points of the agricultural parcels were considered as a raw material supply point. The points (centroid coordinate of the polygon) revealed as a result of land suitability analysis were considered as candidate power plant points and residential areas whose household is greater than 40 were taken as the hot and cold heat demand points. The electricity generated in the power plant was transmitted to the nearest high voltage line. Therefore, the Euclidean distance matrix from the centroid points of the parcels to the candidate power plant points, from the power plants and to the electricity line and the settlements were created.

3.4. Current situation

There are villages, main roads, rivers, high voltage electricity transmission lines, and water channels on the overall Bismil map as shown in Figure 2a. Cotton and corn are grown on the irrigable land, which covers the south part of the reference line as given in Figure 2b. Agricultural parcels in which only cotton and corn are grown were considered as a raw material supply point. Thus, parcels, which are in the south of a reference line, which is 10 km north of the water channel, were taken. On the other hand, the entire Bismil map was considered for determining candidate power plant points and settlements. A power plant can be established in the north or south part of the reference line or a settlement located in the north or south part of the reference line can get heat energy. However, parcels in the south part of the reference line can be a supply point as cotton and corn can be grown in these parcels.

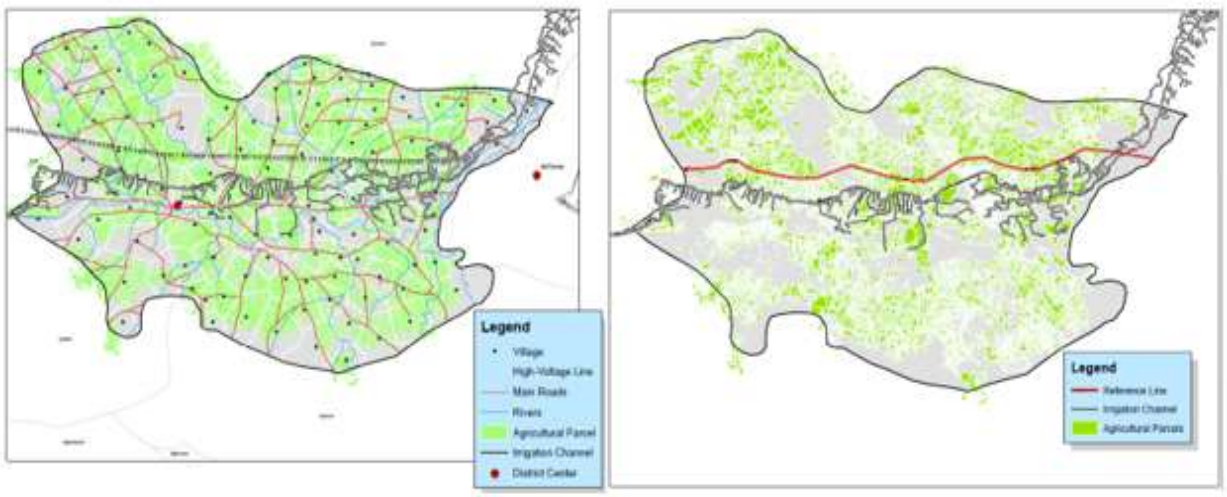

Fig. 2. Current situation (a,b)

3.5. Land suitability analysis

The geographical information system has spatial analysis tools to draw meaningful conclusions from the map data. At this point, the suitability analysis used in site selection analysis was applied to the agricultural terrain of Bismil, Diyarbakır, Turkey to determine the suitable candidate power plant locations. The suitability analysis consists of two sub-analyses called suitability model and restriction model. The formulation of the suitability analysis is as follows in Equation 1.

$$si = \prod_{j=1}^{m} r_j \sum_{i=1}^{n} w_i C_i \quad (1)$$

Where

si = Suitability index
r_j = Boolean value (0,1) of j^{th} criteria in restriction model
m = Number of the criteria in the restriction model
w_i = Weight assigned to the i^{th} preference criteria in suitability model
c_i = Value of the i^{th} preference criteria in suitability model
n = Number of the preference criteria in suitability model

In Equation 1, the restriction model is set by giving Boolean value (0,1) to certain criteria (j). The restricted cells (90x90 m) are represented by 0, while viable cells are represented by 1. As for in the second part, the suitability model is set by giving weights to certain criteria (i). In the next stage, both layers (suitability and restriction) are overlaid (multiplied) and the grid (raster) cells whose suitability analysis result (s) equals to zero are excluded. This means that these grid cells are not suitable according to a certain criterion. In other words, grid cells whose suitability values are greater than zero are considered as suitable. Equation 1 is applied to all the cells. After that, the most suitable ones among the suitable lands are selected based on a certain criterion (suitability value of the cell, the size of the land).

3.5.1. Restriction model

In the restriction model, the soil map layer and water body layer obtained from the Ministry of Agriculture and Forestry and General Directorate of State Hydraulic Works in Turkey were utilized. The restriction model aims to restrict the selection area as much as possible and fulfills

some legislative and environmental obligations. The excluding criteria were demonstrated in Table 1. The location of the bioenergy facility must be at least 250 meters away from the settlements due to renewable energy law. Facility location must be also at least 150 meters away from water bodies such as lake, river and irrigation channels. This constraint enables facility infrastructure more durable. The two buffer zones were established to meet constraints. Land-use types such as inadequate drainage, flood plains, vineyards and olive groves on the soil map layer were excluded in the model. All these limitations were coded on the raster cells with a size of 90x90 m through Boolean values. The excluding and including cells were revealed by multiplying the related raster layers using Equation 2.

$$rv = (r_{buffer(settlement)} r_{buffer(water)} r_{soil\ map}) \quad (2)$$

Where *rv* represents the restriction value of the cell. $r_{buffer(settlement)}$, $r_{buffer(water)}$ and $r_{soilmap}$ denote the boolean value of three criteria, respectively. For instance, if a cell is 250 m far away from the settlement, then its value takes 1 as it is viable for the construction of a power plant in the restriction model.

Table 1. The set of exclusion criteria used in restriction model

Settlement	Water	Soil Map
250 m (buffer)	150 m (buffer)	"DCV IN ('YR' , 'YT')", "DTO IN ('y') OR SAK IN ('S', 'V', 'Vs', 'B', 'Bs', 'O', 'Za', 'Zç', 'Zz', 'Zf', 'Zk', 'Zm', 'Zt', 'Zp', 'Zi', 'Zd') OR AZT IN ('IY', 'SB', 'DK') OR AKK IN ('I' , 'II') OR ATS IN ('w') OR DCV IN ('GL' , 'HV' , 'IR' , 'KY' , 'MZ' , 'YR' , 'YS' , 'YT')"

3.5.2. Suitability model

In the suitability model, six preference criteria were weighted according to importance. The distribution of weightiness was determined according to expert judgments. In such cases, the Analytic Hierarchy Process (AHP) method, which is one of the multi-criteria decision-making processes, can be utilized to calculate weight values more scientifically. Proximity to supply points, settlement, main roads and water bodies raster layer, slope raster layer and land use raster layer was employed as an input in this model. The six input rasters were reclassified to a common measurement scale of 1 to 10. 10-point denotes the most favorable preference and vice versa. Each raster layer cell's value was multiplied by a weight of related raster layer and all raster layer datasets were combined to create a weighted overlay layer. The formulations of the

suitability model as given in Equation 3 and the weights of the criteria set as given in Table 2 were shown as follows.

$$sv = \sum_{i=1}^{n} w_{proximitytosupplypoints}\, C_{psp} w_{proximitytosettlement} C_{ps} w_{slope} C_s\, w_{proximitytomainroads} C_{pmr}$$

$$w_{landuse} C_{lu} w_{proximitytowaterbodies} C_{pwb} \quad (3)$$

Where *sv* represents the suitability value of the cell. $w_{proxmitytosupplypoints}$, $w_{proxmitytosettlement}$, w_{slope}, $w_{proxmitytomainroads}$, $w_{landuse}$ and $w_{proxmitytowaterbodies}$ are weight of criteria and indicated in Table 2. c_{psp}, c_{ps}, cs, c_{pmr}, c_{lu} and c_{pwb} denote cell value of every criterion. This value is calculated through data classification methods in ArcGIS.

Table 2. Preference criteria and weights

Proximity to Supply Points	**Proximity to Settlements**	**Slope**	**Proximity to Main Roads**	**Land Use**	**Proximity to Water Bodies**
35%	20%	5%	15%	15%	10%

3.5.3. Final suitability model and most suitable parcels

Multiplying the final restriction raster layer and weighted overlay raster layer created the final suitability layer. Each raster layer cell with a value of zero in the restriction model was also excluded in the final suitability model as expected. The final suitability map is shown in Figure 3a as follows. As can be noticed, the suitable areas are clustered mostly in the south of the reference line due to the high percentage of criteria of proximity to supply points and proximity to water bodies.

After creating the final suitability raster layer, areas with preference scores of 7, 8, 9 and 10 and with a cover area of more than 4 ha were determined as the most suitable candidate points for power plant building. Raster data type was used for scoring preference criteria and vector data (polygon) was used for calculation of the coverage area of separate parcels. Therefore, after the completion of the scoring evaluation, the raster layers were converted to polygons for cover area calculation. According to the predefined criteria (suitability score and surface area), 127 polygons (parcel) were determined as the most suitable lands for power plant construction (see Figure 3b). In other words, there are 127 candidate locations on which a power plant can be constructed.

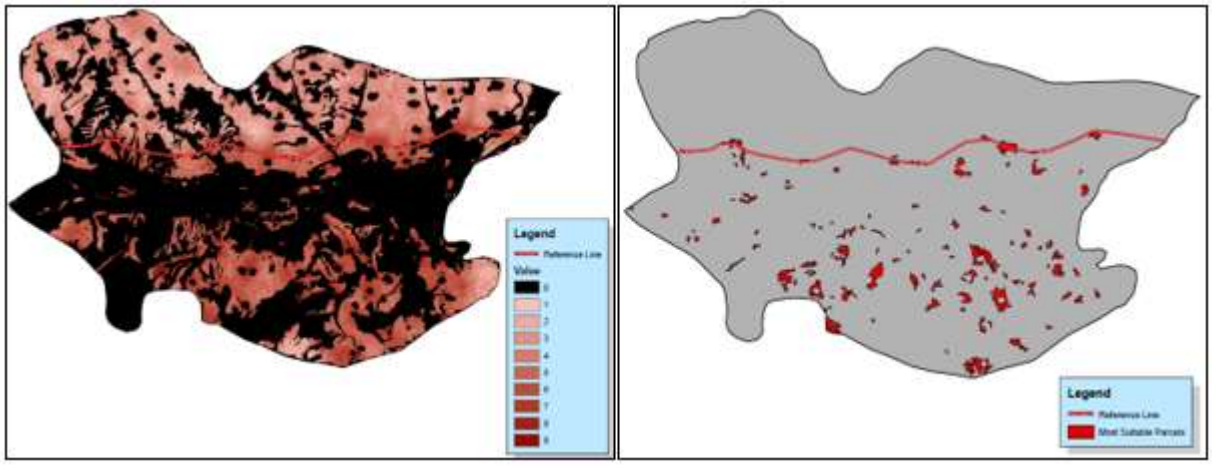

Figure 3. Final suitability map (a), the most suitable parcels (b)

The analysis was completed by incorporating high transmission voltage lines in the model. The settlements shown in Figure 4 whose household number is greater than 40 were considered hot and cold heat demand points in the model. The Euclidean distances between the candidate power plant points and agricultural parcels, candidate power plant points and electricity transmission line, candidate power plant points and settlements were retrieved from the GIS to be employed as a parameter in the meta-heuristic model. The final design in GIS was demonstrated in Figure 4.

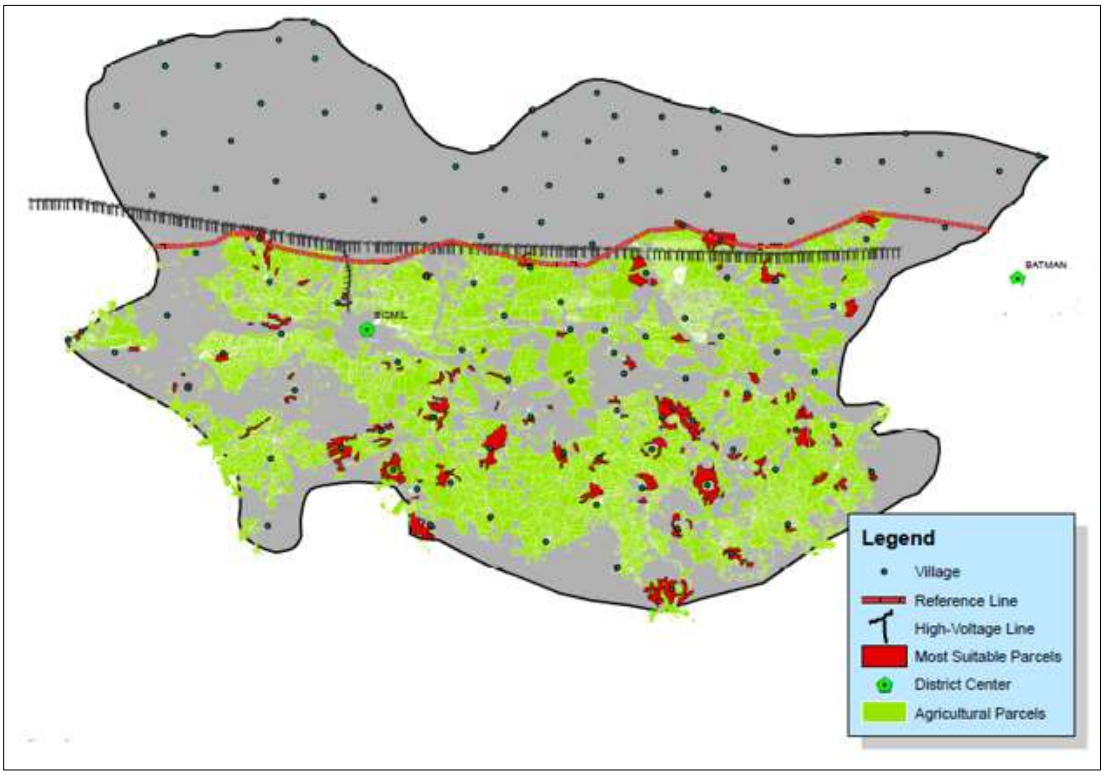

Figure 4. The final design of the proposed GIS model

There are 14,391 parcels and 50 settlements whose population is greater than 50 based on the data retrieved from GIS. Some parcels have a quite small surface area. Therefore, parcels whose

surface area is greater than 20 da were considered not to reduce the efficiency of raw material transportation. Thus, the number of parcels are considered in meta-heuristic decreased 7,784, which covers almost a surface area of 900,000 da. Eventually, 2 distance matrixes with a size of 7,784 x 127, 50 x 127 and a vector with a size of 127 x 1 representing parcels to power plants, settlements to power plants and power plants to the nearest high voltage transmission line were created based on the results of the analyses carried out in GIS.

3.6. Finding the best plant: a case study based on Simulated Annealing

In this section, a simulated annealing heuristic algorithm was developed and applied to Bismil District in Diyarbakır, Turkey. At first, the optimization rate of the proposed heuristic was found by applying it to a small-sized problem, which was solved via a MILP model (Akgül and Seçkiner 2019). After observing that the viability of the simulated annealing heuristic is satisfactory, the actual problem was solved based on the actual data retrieved from GIS.

3.6.1. Simulated annealing algorithm

Simulated annealing (SA) algorithm was developed by Kirkpatrick et al. (1983). The proposed SA algorithm based on the previous algorithm developed by Metropolis et al. (1953). This algorithm simulates the heating and cooling process of a material called annealing. Annealing refers to an analogy with metallurgy. The solid material is heated and slowly cooled back under controlled conditions to improve the strength and durability of the material. At the end of the process, the energy of the atoms decreases, and the structure of the solid material becomes stable. This shows that atoms in the solid material do not move anymore beyond a certain temperature, which refers to the local or global optimum point in the SA algorithm.

SA is a probabilistic meta-heuristic due to having a random initial solution and utilizing a probability when the neighborhood solution is worse than the current solution. The initial and final temperature and gradual cooling rate are taken into account in the annealing process. Better solutions are always accepted unconditionally as expected. Some uphill moves (downhill for maximization), which represent the worse solution, can escape local optima through a probability of $e^{-(Sn-Sc)/T}$, where T is the current temperature, Sc is the current solution (energy) and Sn is the neighbor solution (energy). SA differs from a hill-climbing search algorithm due to making use of this probability to escape local optimal. In such cases where the algorithm finds a worse solution, a uniform random number between 0 and 1 is generated. If that number is less than the probability value, the worse solution is accepted in case there might be better solutions beyond this point. As might be observed from the probability formula, as the

temperature decreases (towards the end), and change in energy decreases, the formula output becomes smaller. So, the chance of accepting worse solutions is decreased. This also means that the system becomes stable towards to end. While the temperature is high, the algorithm can jump out of any local optimums. The higher an initial temperature is determined, the better exploration in the entire search space. However, a high initial temperature increases the computation time.

SA was initially developed for combinatorial problems and then adapted for continuous problems. The unique advantages of SA are its ability to escape from local optima, straightforward implementation, and rapid convergence. In a SA algorithm, the most important factors are initial temperature, the number of moves allowed at each temperature, the cooling rate, and the final temperature at which the search is completed (Castillo-Villar 2014). They are called as control parameters. These parameters should be adapted to the problem dealt with, as the search landscape can be different in every single problem. Besides, fine tunings can be adjusted at a particular step in the algorithm. All these adjustments allow the algorithm to escape local optimums and to find a better solution.

Notations used in SA and their pseudo-codes are demonstrated as follows.

Notations:

X_0 = Initial random solution

X_i = Current solution

X_{i+1} = Potential (Neighbor) solution

X_b = Best solution

T_0 = Initial temperature

T_t = Temperature at stage t

T_f = Final temperature

a = Cooling rate

N_n = Number of moves at each temperature

σ = Move operator

Pseudocode for simulated annealing

Step 1: Set X_0, T_0, T_f, a, N_n and σ

Step 2: Start at a random point in the search space

Step 3: $X_b = X_i$

Step 4: Move to another location by using the move operator, σ

Step 5: Look neighborhood points around the current solution point and move to one of these points,

$n = 1$

Step 6: If $f(X_{i+1})$ is better, take it as current solution, $X_i = X_{i+1}$

If $f(X_i)$ is better than $f(X_b)$, $X_b = X_i$

Step 7: If not, generate a random number between 0 and 1 and check the random number is less than $e^{\frac{-(f(X_{i+1})-f(X_i))}{Tt}}$

Step 7.1: If less, take it as the current solution, $X_i = X_{i+1}$

Step 7.2: If greater, don't take it and stay where you are and look around the current point

Step 7.3: $n = n + 1$

Step 8: Repeat steps 5 to 7 while $n \leq N$

Step 9: $T_{t+1} = a \; x \; T_t$

Step 10: Repeat steps 5 to 9 while $T_t \leq T_f$

Step 11: Return X_b

There are 7,784 parcels and 50 settlements and 127 candidate power plant sites in the actual problem. Raw materials are transported from the parcels to the power plant and after processing in a power plant, generated electricity is transmitted to the nearest high voltage power line, and heat is transferred to settlements. The algorithm, which runs while moving neighbor point from the current point (fifth step in pseudo-code) demonstrated as follows;

- Select a set of random power plants as an initial solution
- Transport raw material from the parcel to the nearest location where a power plant established
- Transfer hot heat produced from the power plant/s to the settlement which has the highest heat demand[1]
- If remained hot heat produced from power plant/s is greater than the highest heat demand among the settlement which has not received hot heat, transfer hot heat to the settlement which has the highest heat demand among the settlement which has not received hot heat yet
- Repeat the fourth step until remained hot heat is less than the highest heat demand among the settlement which has not received hot heat
- Transfer remained hot heat to the settlement which has the highest heat demand among the settlement which has not received hot heat

[1] Monte Carlo Simulation was employed to determine which strategy is more attractive. The result indicates that providing heat to settlements in descending heat demand order is more convenient than ascending order.

- Transfer cold heat produced from the power plant to the settlement which already received hot heat
- If remained cold heat greater than the highest cold heat demand among the settlement which has not received cold heat, transfer cold heat to the settlement which has the highest cold heat demand among the settlement which has not received cold hot heat yet
- Repeat the eighth step until remained cold heat is less than the highest cold heat demand among the settlement which has not received cold heat
- Transfer remained cold heat to the settlement which has the highest heat demand among the settlement which has not received cold heat
- Transmit electricity from the power plant to the nearest high voltage line
- Calculate the net present value

It was allowed that partial demand of the settlement could be satisfied. If a pipeline network is constructed between the power plant and settlement for hot or cold energy transmission and if there is remainder heat, it can be sold the settlement for which a pipeline network exists.

3.6.2. Assumptions

In this study, the average amount of agricultural residue of two years was considered for every year in the project lifetime. Thus, there will be the same amount of income and outcome (cash flow) for every year in this study. However, cash flow was considered a fixed value combining two successive years in the project lifetime in the previous study. Accordingly, project lifetime was considered as 20 years and the discount rate was taken as 10.914 in this study. Aside from this difference, two assumptions were included existed assumptions as described in our previous study (Akgül and Seçkiner 2019). The first assumption is that raw material in a parcel is allowed to transport only one power plant. It means a parcel can be assigned just one power plant. The second assumption is that a settlement is allowed to receive heat from just one power plant.

3.6.3. Indices, parameters, equations and control parameters

Indices and parameters were given in our published study (Akgül and Seçkiner 2019). 7784 parcels, 127 candidate power plant points and hot and cold energy demand points are represented as *j, k and l* indices respectively in this study. The parameters are exactly as same as the

parameters given in that cited study. We invite readers to read our previous study to eliminate the repetition of too many similar parameters in this study. Apart from those parameters specific to our previous study, some extra parameters were determined in this study due to the first assumption mentioned in the section of 6.2.1. Additional parameters were indicated as follows;

Additional Parameters:

C_{kj} and G_{kj}: The annual average amount of the hot/cold heat obtained by the k^{th} settlement from the power plant at the j^{th} candidate point. The annual average amount of the hot/cold heat is calculated based on the produced amount of hot/cold heat in the first and second year,

F_{kj} = It equals to 1 if k^{th} settlement gets the hot or cold heat from the plant located at the j^{th} candidate point, 0 otherwise,

IP_j: Annual average installed power of power plant established in the j^{th} candidate point (MW). Annual average installed power is calculated based on the generated power in the first and second year

K_{ij} = It equals to 1 if the raw material is transported from i^{th} parcel to the plant located at j^{th} candidate point, 0 otherwise,

Mak_{kj}: The unit amount of hot and cold heat flow between k^{th} settlement and power plant at the j^{th} candidate point (MW_{heat}/h). If a settlement gets hot and cold heat, a greater amount is considered to construct pipeline as expected

SA_i: Annual average supply amount of the raw material from the i^{th} parcel (ton), $SA_i = PA_i X \frac{YPSK_{1i} + YPSK_{2i}}{2}$, $i = 1 \ldots 7784$,

X_{kj} = It equals to 1 if k^{th} settlement gets hot heat from the plant located at the j^{th} candidate point, 0 otherwise,

Y_{kj} = It equals to 1 if k^{th} settlement gets cold heat from the plant located at the j^{th} candidate point, 0 otherwise,

Here, the low heating value of the agricultural products (LHV), the yield of those products per km^2 (YPSK), organic dry matter rate of those products (ODMR) and unit raw material price of those products (URMP) were given in Table 3. This table can be regarded as a crop pattern of the whole agricultural land handled in this study. This cropping pattern is repeated interrelated through project lifetime. It means that if corn is cultivated on the i^{th} parcel in the first year, cotton will be cultivated in the second year on the same parcel.

Table 3. Harvested crops and their attributions

Parcel No	PA_i	Type of the agricultural crop harvested in the first year	Type of the agricultural crop harvested in the second year	$YPSK_{1i}$ (ton/km^2)	$YPSK_{2i}$ (ton/km^2)	$ODMR_{1i}$ (%)	$ODMR_{2i}$ (%)	LHV_{1i} (Mwh/ton)	LHV_{2i} (Mwh/ton)	$URMP_{1i}$ (euro/ton)	$URMP_{2i}$ (euro/ton)
i_1	80	Cotton	Corn	0,30	0,25	0,50	0,85	4,78	4,68	20	40
i_2	55	Corn	Cotton	0,25	0,30	0,85	0,50	4,68	4,78	40	20
i_3	80	Cotton	Corn	0,30	0,25	0,50	0,85	4,78	4,68	20	40
…	…	…..	…..	…..	…..	…..	…..	…..	…..	…..	…..
i_{7784}	89	Corn	Cotton	0,25	0,30	0,85	0,50	4,68	4,78	40	20

Equations:

Approximately an installed power of 29 MW can be produced from corn and cotton residues in the field based on the real data. Distribution of the whole power to candidate power plants is determined by the SA algorithm through comparing trade-offs between various inputs such as transportation cost of raw material, transmission cost of heat and electricity, the unit installation cost of the power plant and pipeline network. Seasonal fluctuations were considered for calculation of power plant and pipeline network installation cost.

Installed power is calculated in Equation 4 given as follows:

$$IP_j = \begin{cases} 0 & , K_{ij} = 0 \\ \left(\sum_{i=1}^{i=7784} \frac{(SA_{1i} * LHV_{1i} + \mathrm{ODMR}_{1i}) + (SA_{2i} * LHV_{2i} + \mathrm{ODMR}_{2i})}{2}\right) \times \mathrm{EE} \times \mathrm{GE} \times \frac{\mathrm{RMDR}}{\mathrm{OH}}, & K_{ij} = 1,\ j = 1 \ldots 127 \end{cases} \quad (4)$$

Power plant installation cost is calculated in Equation 5 given as follows:

$$\mathrm{PPIC}_j = \begin{cases} 0 & , IP_j = 0 \\ 3.975.198{,}31 + 568.456{,}61 \times \mathrm{IP}_j \, x \, EHDR, & IP_j > 0,\ j = 1 \ldots\ldots 127 \end{cases} \quad (5)$$

Power plant total installation cost is calculated in Equation 6 given as follows:

$$\mathrm{PPTIC} = \sum_{j=1}^{j=127} \mathrm{PPIC}_j \ , \quad (6)$$

Power plant annual average operation and maintenance cost is calculated in Equation 7 as follows:

$$\mathrm{PPOMC} = \mathrm{PPTIC} \times \mathrm{PPOMCR}, \quad (7)$$

Power line installation cost per kilometer from the k^{th} settlement to the j^{th} candidate power plant point, which is generated from a regression model based on unit flow, and $DSP_{k,j}$, is calculated in Equation 8 as follows:

$$\text{PLICPK}_{kj} = \begin{cases} 0 & , F_{kj} = 0 \\ 8.193{,}78 + 3.586{,}11 \text{ X Mak}_{kj} \; x \; X \; EHDR, & F_{kj} = 1, k = 1\ldots50, j = 1\ldots.127 \end{cases} \quad (8)$$

Power line network total installation cost and annual average power line network operation and maintenance cost are calculated in Equation 9 and 10 given as follows:

$$\text{PLNTIC} = \sum_{k=1}^{k=50} \sum_{j=1}^{j=127} \text{PLICPK}_{kj} \text{ x } \text{DSP}_{kj}, \quad (9)$$

$$\text{PLNOMC} = \text{PLNTIC x PLOMCR}, \quad (10)$$

Electricity transmission total installation cost is calculated in Equation 11 given as follows:

$$\text{ETTIC} = \begin{cases} \left(\sum_{j=1}^{j=127} DPETL_j \; X \text{ ETLICPK}\right) + 2.000.000{,}00, 0 < IP_j \leq 20, \\ \left(\sum_{j=1}^{j=127} DPETL_j \; X \text{ ETLICPK}\right) + 2.800.000{,}00, IP_j > 20, \\ 0, \; IP_j = 0 \end{cases} \quad (11)$$

Annual average raw material transportation cost is calculated in Equation 12 given as follows:

$$\text{RMTC} = \begin{cases} 0, K_{ij} = 0 \\ \left(\sum_{i=1}^{i=7784} \sum_{j=1}^{j=127} \text{ x DPP}_{ij} \text{ x } \text{SA}_i\right) \text{ x URMTC}, & K_{ij} = 1 \end{cases} \quad (12)$$

Annual average hot and cold heat transportation cost is calculated in Equation 13-14 given as follows:

$$\text{HHETC} = \begin{cases} 0 \, , X_{ij} = 0 \\ \left(\sum_{k=1}^{k=50} \sum_{j=1}^{j7} \text{C}_{kj} \text{ x } \text{DSP}_{kj}\right) \text{ x HTCPK}, & X_{ij} = 1 \end{cases} \quad (13)$$

$$\text{CHETC} = \begin{cases} 0 \, , Y_{ij} = 0 \\ \left(\sum_{k=1}^{k=50} \sum_{j=1}^{j=127} \text{G}_{kj} \text{ X } \text{DSP}_{kj}\right) \text{ X HTCPK}, \; , \; Y_{ij} = 1 \end{cases} \quad (14)$$

Annual average electricity loss cost through transmission is calculated in Equation 15 given as follows:

$$\text{ETLLC} = \begin{cases} 0, \; , IP_j = 0 \\ \sum_{j=1}^{j=127} \left(IP_j \text{ X EP X OH X } (1 - \text{ECRIP})\right) \text{ X } \left(1 - \text{ ELM}_j\right), & IP_j > 0 \end{cases} \quad (15)$$

Annual average raw material cost is calculated in Equation 16 given as follows:

$$\text{RMC} = \sum_{i=1}^{i=7784} \frac{\text{SA}_{1i} \text{X URMP}_{1i} + \text{SA}_{2i} \text{ X URMP}_{2i}}{2} \quad , \quad (16)$$

Annual average revenues from electricity sale, hot heat sale, cold heat sale and fertilizer sale are calculated Equation 17-20 given as follows:

$$\text{ES} = \sum_{j=1}^{j=127} \text{IP}_j \text{ x EP x OH x (1-ECRIP)}, \quad (17)$$

$$\text{HHES} = \begin{cases} 0 \, , X_{ij} = 0 \\ \left(\sum_{k=1}^{k=50} \sum_{j=1}^{j=127} \text{C}_{kj} \text{ x } \text{RHRAL}_{kj}\right) \text{ x HHEP}, & X_{ij} = 1 \end{cases} \quad (18)$$

$$\text{CHES} = \begin{cases} 0\,, Y_{ij} = 0 \\ \left(\sum_{k=1}^{k=50} \sum_{j=1}^{j=127} \text{G}_{kj} \text{ x } \text{RHRAL}_{kj}\right) \text{x CHEP}, Y_{ij} = 1 \end{cases} \quad (19)$$

$$\text{FS} = \left(\sum_{i=1}^{i=7784} \frac{SA_{1i} \text{ X ODMR}_{1i} + SA_{2i} X\ ODMR_{2i}}{2}\right) \text{x RMDR} \times FR \times FP, \quad (20)$$

Power plan initial variable cost, annual average electricity sale, fertilizer sale, and raw material cost are pre-calculated as they are independent of supply chain design. For this reason, these costs and income items were excluded in the SA algorithm.

Control Parameters :

As abovementioned, control parameters determine the viability of the SA algorithm. They should be adjusted according to the case. In this study, initial temperature and final temperature were determined based on the formulas presented in a published study (Seçkiner 2005).

Initial temperature (T_0) was calculated in Equation 21 given as follows:

$$T_0 = \frac{f_{max} - f_{min}}{lnP_i} \quad (21)$$

Where f_{max} and f_{min} represent the maximum and minimum value of the fitness function, P_i represents the acceptance probability of the solutions at the initial temperature. The final temperature was calculated similarly based on P_f which represents the acceptance probability of the solutions at the final temperature.

Temperature is reduced geometrically based on formula demonstrated in Equation 22 given as follows. Every change in temperature denotes iteration in the SA algorithm.

$$T_{t+1} = T_t \ x \ a \quad (22)$$

In the beginning, the initial temperature is taken as a high value and a few hundred moves are carried out at this temperature (Kirkpatrick 1983). The probability score (P_i), which is given by the user at the beginning, is compared to the ratio of accepted moves to all attempted moves. If P_i is greater than the ratio, this temperature is considered initial temperature; otherwise, multiplying two increases initial temperature value. This approach was employed for the calculation of the initial temperature in the proposed meta-heuristic. The final temperature can be calculated similarly.

3.6.4. Fitness Function

As abovementioned, factors that do not affect the solution was excluded in meta-heuristic. For instance, revenue from fertilizer sale is obvious regardless of solution quality. For the sake of

simplicity, these factors were not included in the SA algorithm. Instead, they were appended at the end of the algorithm to display the total net present value. Thus, the objective function formula was shortened. The objective function was formulated in Equation 23 as given follows:

$$\text{Max (NPV)} = D_{(i,n)} \times (\text{HHES} + \text{CHES} - \text{RMTC} - \text{HHETC} - \text{CHETC} - \text{PPOMC} - \text{PLNOMC} - \text{ETLLC}) - \text{PPTIC} - \text{PLNTIC} - \text{ETTIC} \quad (23)$$

Where HHES, CHES, RMTC, HHETC, CHETC, PPOMC, PLNOMC, ETLLC, PPTIC, PLNTIC, ETTIC represent hot heat energy sale, cold heat energy sale, raw material transportation cost, represent hot heat energy-transportation cost, cold heat energy-transportation cost, operation & maintenance costs of power plant and pipeline network, electricity transmission line loss cost, power plant, pipeline network, and electricity transmission total installation cost, respectively.

Before the construction of the algorithm, the neighborhood search strategy, which is the crucial part of a SA algorithm, was determined. The proposed algorithm selects a neighbor solution by generating a random integer number, which has a uniform distribution between 1 and 127. Each number represents a candidate power plant location. If there is a power plant at the location of the generated number, the power plant is not installed and it's a value (1) is switched to 0 and vice versa.

After determining neighbor search strategies, two solution approaches were developed. In the first approach, the entire search space was explored to understand the trajectory of the solution based on the number of power plants. There is not constraint associated with a number of the power plant in this algorithm. All of the 127 power plants can be established. In this algorithm, initial temperature and final temperature were calculated based on the best and the worst solution. The algorithm intents to most likely establish one power plant to maximize net present value. This makes sense since the fact that fixed establishment costs such as power plant installation cost; power line installation cost and transformer cost are rather high. These costs can reach up to 6 million euros for every power plant. The other reason for such a trend of the algorithm is the lowness of raw material transportation cost. Those two factors mainly influence the algorithm trajectory.

Control parameters were adjusted for the first case. P_i and P_f were taken as 0.96 and 0.01, respectively. The number of moves for each temperature was taken as sufficiently large value to search the entire space. In the first SA algorithm, it was taken as 1000.

The control parameters of the first approach were presented as follows.

T_0 = 145, It was calculated based on the Eq. 21.

T_f = 1, It was calculated based on the Eq. 21.

a = 0.95, It was predetermined.

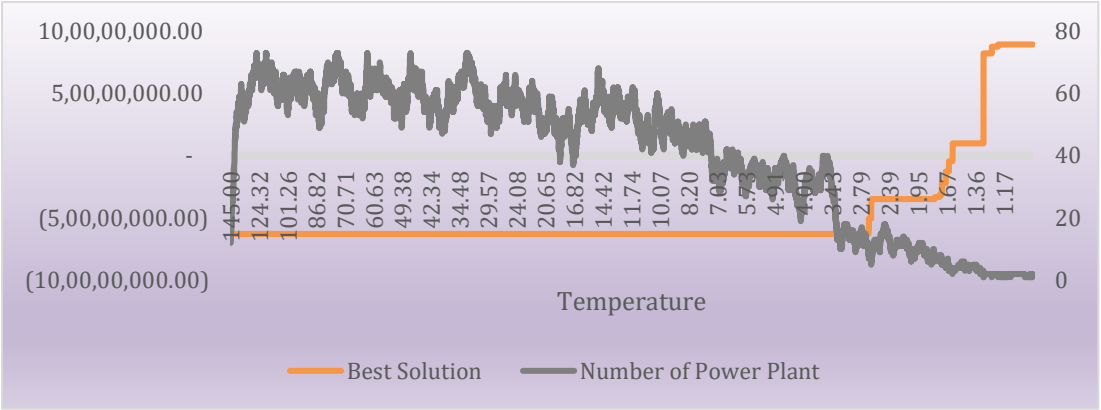

Figure 5. Treatment of the SA algorithm based on the first approach

Just one power plant was installed at the point where net present value peaks based on the result. This reveals that establishing more than one power plant restrain finding a better solution. It was decided that one power plant establishment most likely seems to an optimum solution. Then, the second algorithm, which narrows the solution space, was developed. In this algorithm, one power plant was set in the initial solution and a power plant was selected randomly as a neighborhood search. The probability of selecting each power plant has a uniform distribution. If the selected power plant is set already as 1, then it was set as 0 and vice versa. Thus, it was allowed that just one power plant could be established. In the second approach, T_0 and T_f were recalculated since the minimum value of fitness function was changed. In this algorithm, the number of moves (N) was taken 127, which equals to the number of variables (power plant). Control parameters which were used in the second algorithm were demonstrated as; T_0 = 224; T_f = 1; a = 0,95; N = 127; P_i = 0.96; P_f = 0.01.

The proposed algorithm was run on an Intel Core Quad 2.4 GHz CPU with 8 Gb Ram on a 64-bit platform a few times and the best solution was found in every execution. The computational time took almost 180 seconds on average. The iterative treatment of the algorithm was demonstrated in Figure 5-6 as given follows;

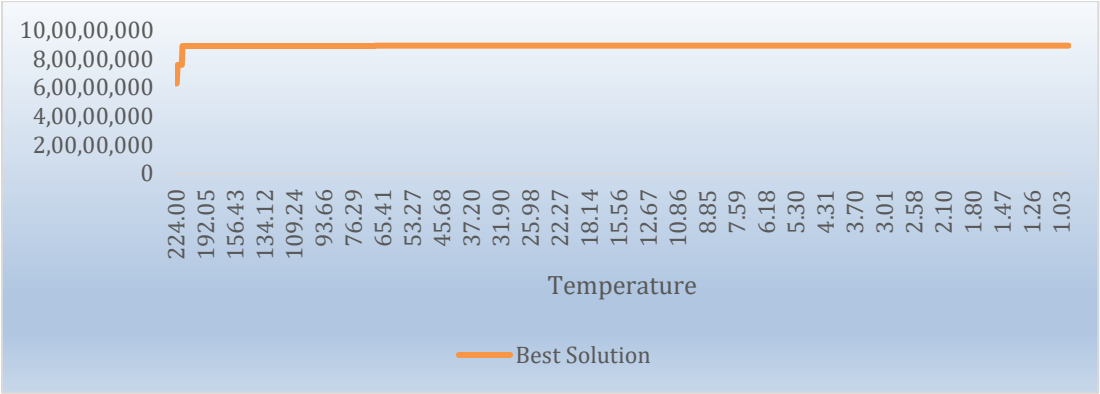

Fig 6. Treatment of the SA algorithm based on the second approach

Based on the result, the second algorithm got the same result just as the first algorithm. Narrowing the search space reduced the computational time by nearly 90%.

4. The results and discussion

Based on the results of the SA model, just one power plant with an installed power of 29,09 MW has been established. It can be concluded that high installation cost a power plant and the low unit cost of raw material transportation has a strong impact on the establishment of just one power plant. 0.15 % of the electricity produced is lost due to the distance between the power plant and the nearest connection point. The nine settlements for which the hot heat energy was supplied also received the cold heat energy. The eight settlements receive their whole hot heat demand, while 1 settlement receives 5 % of its hot heat demand. 41 settlements receive only cold heat energy. The reason behind the fact that more settlements received cold heat energy is relatively high price and low demand for cold heat energy compared to hot heat energy. All settlements completely received their cold heat demand. The amount of heat produced is highly greater than the total cold heat demand of all settlements even if losses are considered.

99.33 % of the produced hot heat was sold to settlements, however, 80.43 % of the hot heat demand was met. 66.86 % of the cold heat was sold to settlement and cold heat demand was met completely. 0,67 % of the hot heat, 1.3 % of the cold heat and 0.37% of the electricity were lost while transferring. On the other hand, proportional distributions of income and expenses through project lifetime were illustrated in Figure 7 as follows. As might be seen from the figure, electricity sales in revenue items and power plant establishment cost in expenditure items are by far the most effective factors than others.

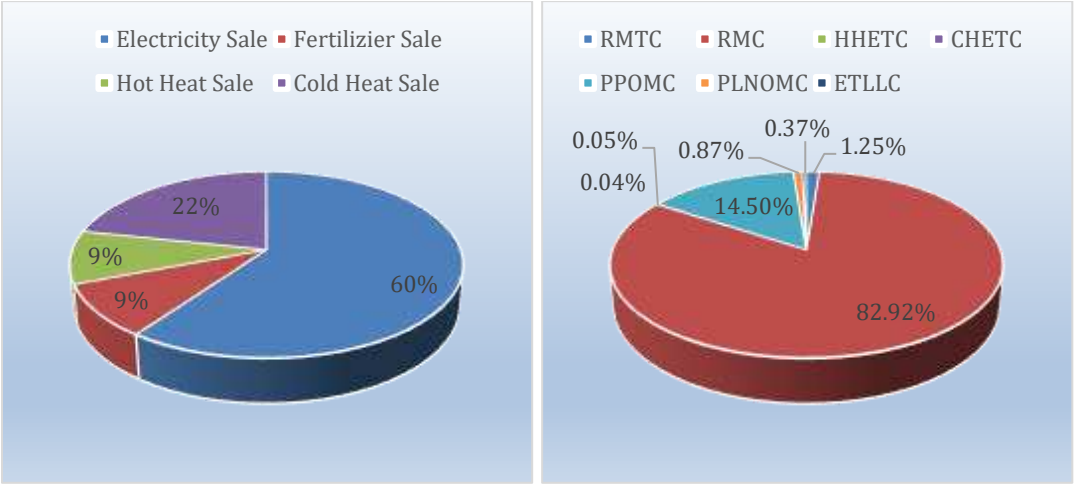

Figure 7. The revenues by product and expenditures by operations (SA Algorithm)

The share of raw material transportation cost (RMTC) is relatively low as might be observed from Figure 8. This resulted from quite a low cost of unit transportation cost of raw material and the short distance between parcels and power plants. Besides, electricity transmission line cost (ETLLC), hot and cold heat transferring cost (HHETC and CHETC) are relatively low since proposed power plant locates very close to the city center, where demands the major portion of the total heat, and power line, respectively (see Figure 8).

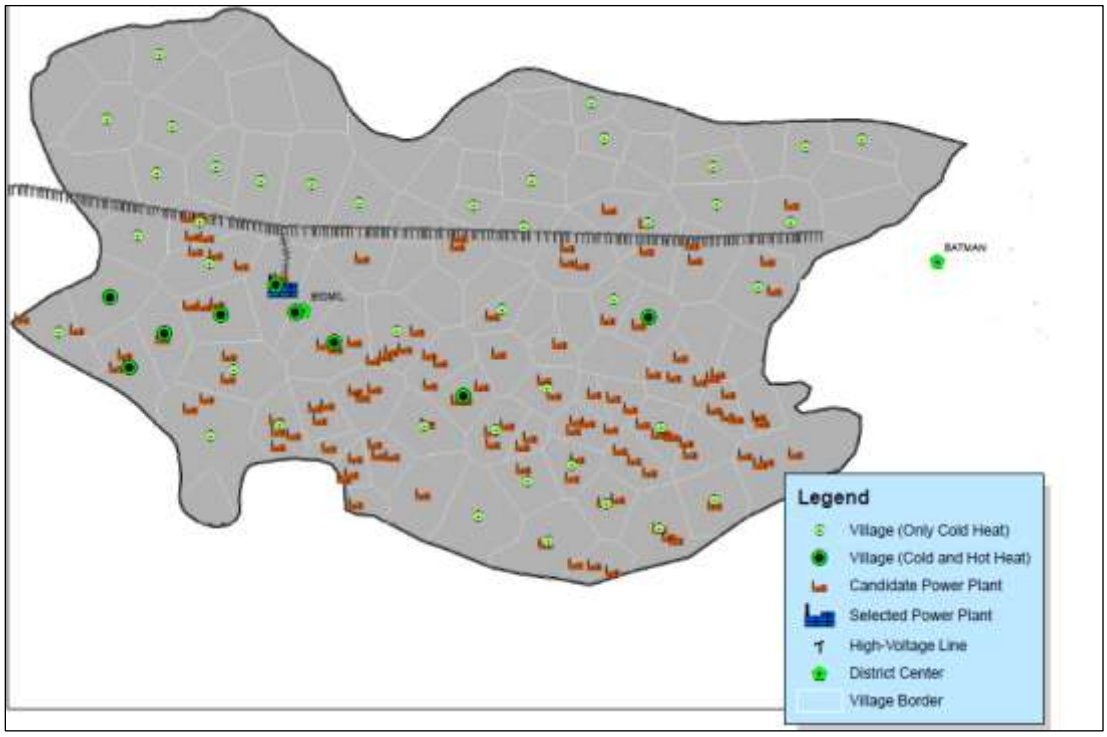

Figure 8. Final depiction of the problem

5. Conclusion

In this study, a GIS based simulated annealing algorithm has been proposed and applied to a real-world problem (Bismil District in Diyarbakır, Turkey). The results are promising in terms of the performance of the SA algorithm and attractive for a potential investment. Large-scale combinatorial problems related to bioenergy supply chain problems can be solved by utilizing the proposed SA heuristic. The treatment of the proposed algorithm was observed in an extensive search space. The algorithm was run many times with a different set of control parameters to exactly understand solution trajectory. The experiments showed that the installation of one power plant is the optimum.

This study is the first in terms of utilizing simulated annealing in a trigeneration system, which is designed for the biomass-to-bioenergy supply chain. For future studies, assumptions of this model can be improved. and in this way, a real-world problem can be dealt with more realistically. In addition to assumptions, control parameters of the proposed SA algorithm could be adjusted based on different strategies. Besides, a population-based algorithm can be utilized in the bioenergy supply chain in cases wherein trade-offs are very decisive.

Financial support for this work was provided by the Gaziantep University, Department of Scientific Research Projects. This support is gratefully acknowledged. Grant number: MF.YLT.17.14.

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