Chapter 10
Comparison of Bat and Fuzzy Clusterization for Identification of Suitable Locations for a Small-Scale Hydropower Plant

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Abstract Hydroelectric plants are an environmentally friendly renewable energy source, but, due to uncertainties in flow patterns, often such energy generation projects fail. Also, deliberations from displaced people and environmental activists (due to large-scale disturbances to the natural ecosystems of adjacent areas) make some highly efficient hydropower projects unfeasible. That is why the success of hydropower projects depends largely on the selection of location. Currently, the efficiency of selecting the ideal locations depends mainly on expert opinion or linear models and other decision-making methodologies where human judgment and opinion play a major role in the reliability of the selection. But, as usual, the error rate in such procedures is generally unsatisfactory. The present study tries to apply clusterization algorithms to identify ideal locations for small hydropower plants in such a way that the need for expert or opinion can be reduced. In the clusterization of a suitable hydropower location, the food foraging behavior of bats and fuzzy-logic-based theory of maximization were applied to a sample population of locations available for hydropower generation including a on where a hydropower plant had already been installed and was operating at rated capacity. The efficiency of the algorithm in identifying this location was analyzed to determine the suitability of the algorithms in estimating the ideal location for hydropower plants. The results showed that both approaches were able to identify the most suitable location, but when the time taken to make the identification was taken into account, fuzzy logic was found to perform better than the bat algorithm as the former took only one iteration to identify the location, whereas the latter needed six iterations but the sensitivity with which the algorithms identified the ideal location was better for bat than fuzzy.

Keywords Clusterization • Hydropower location selection • Fuzzy logic • Bat algorithm

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10.1 Introduction

Hydropower is one of the most reliable sources of energy production and does not require the use of fossil fuels. Although hydropower plants (HPPs) do not cause pollution and hydropower can be found in abundance, the problem of displacement of local populations, changes in land use and land cover of adjacent regions, and, above all, the unreliability of flow in river networks often discourage city planners from moving toward such sources of power.

This problem can be solved if the selection of a location is performed in a logical, scientific, and innovative manner whereby an area with a steady flow throughout the year but minimum displacement in population and minor disturbance to the ecosystem can be selected. But such a location is difficult to find, and generally designers must compromise on one aspect to take advantage of others. But it is essential to identify an optimal solution where wastage will be minimized but utilization of resources will be maximized.

10.1.1 Indian Scenario of Energy Distribution

India, the location of this study, has an installed power generation capacity of approximately 148,000 MW in which thermal power plants powered by coal, gas, naphtha, or oil account for approximately 66% of power generation. Hydropower is by far the single largest renewable energy source in India, accounting for more than 10% of total electricity generation. Most of this energy is from large hydroelectric plants. Renewable sources of energy other than large-scale hydropower have a 7% share, with wind power accounting for the largest share, approximately 5.29% (World Energy Assessment, UNDP (1998) and REN21 (2011a, b)).

The total additional power generation capacity planned for the 11th and 12th 5-year plans (2007–2017) is approximately 150,000 MW, of which the share of renewables such as wind, solar, biomass, and small hydro is slated to reach approximately 10% (i.e., 15,000 MW).

India is ranked fifth with respect to hydropower potential where the total economically exploitable hydropower potential is found to be 148,700 MW of installed capacity, of which the Brahmaputra basin has the largest (66,065 MW) and the Central India River system has the least (4,152 MW) potential to generate hydroelectricity. The Indus basin (33,832 MW) of Punjab and the Ganga basin (20,711 MW) are the two next largest locations with the potential for generation of hydroelectricity.

In addition, 56 pumped storage projects have been identified with a probable installed capacity of 94,000 MW. The hydro potential from small, mini, and micro schemes has been estimated to be equal to 6,782 MW from 1,512 sites. Thus, the total hydropower potential of India is found to be 250,000 MW. The total installed hydropower generation capacity of India is 36,878 MW. That means only 24.80% of the total hydroelectricity potential is being utilized. Bhakra Dam and Nagarjuna are the two major large-scale HPPs in India; they produce nearly 1,100 and 960 MW, respectively, of hydropower annually.

In India, hydropower projects with a station capacity of up to 25 MW each fall under the category of small hydropower (SHP), which is estimated to have a potential of 15,000 MW. The total installed capacity of small hydropower projects (up to 25 MW) as of 31 March 2009 is 2,429.77 MW from 674 projects, and 188 projects with aggregate capacity of 483.23 MW are under construction. That means only 16.2% of the total SHP potential is presently being utilized. The state of Karnataka, with its 83 SHP projects, generates hydroelectricity equal to 563.45 MW. India has 83.8% of SHP potential still to be utilized and has many other areas where the potential of SHP is yet to be identified.

10.1.2 Types of Hydropower Plants

Hydropower plants are generally classified based on quantity of water, water head, and nature of load.

10.1.2.1 Classification by Quantity of Water

HPPs can be classified by the amount of water used as follows:

Runoff River Plants Without Pondage

These plants have no provisions for storing water and use water as and when available. Thus, they are dependent on the rate of flow of water; during the rainy season a high flow rate might mean a certain amount of water goes to waste, while during low runoff periods, due to low flow rates, the generating capacity will be low.

Runoff River Plants with Pondage

In these plants, pondage permits storage of water during off-peak periods and use of this water during peak periods. Depending on the size of pondage provided, it may be possible to cope with hour-to-hour fluctuations. This type of plant can be used on parts of the load curve as required and are more useful than plants without storage or pondage.

This type of plant is comparatively more reliable, and its generating capacity is less dependent on the available rate of water flow (Fig. 10.1).

Reservoir Plants

A reservoir plant is one that has a reservoir large enough to permit carrying over storage from the wet season to the next dry season. Water is stored behind a dam and is available on a regulated basis to the plant as required. The plant firm capacity can be increased and can be used either as a base load plant or as a peak load plant as required. The majority of hydroelectric plants are of this type.

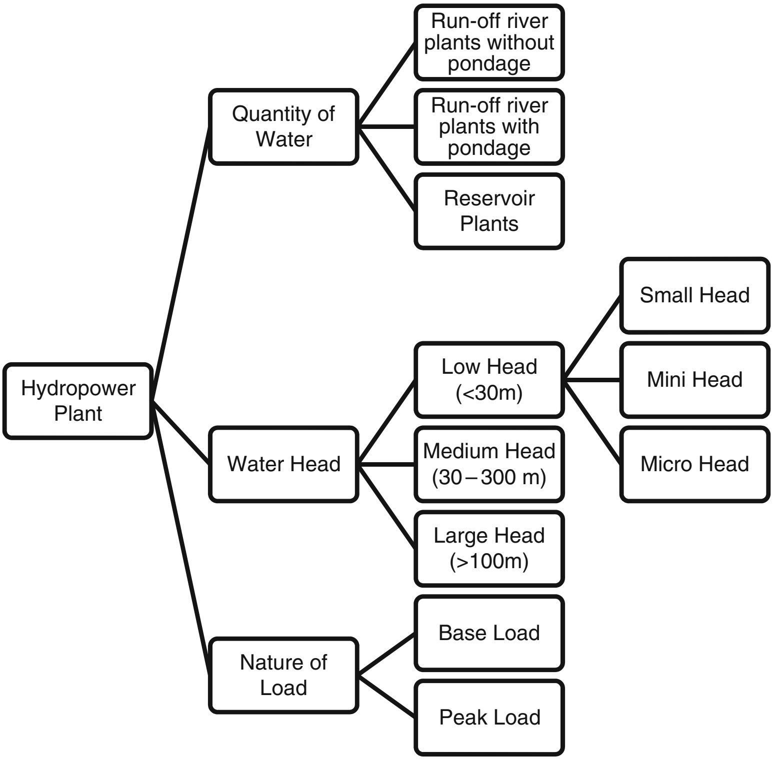

Fig. 10.1 Classification of HPPs with respect to various attributes

10.1.2.2 Classification by Availability of Water Head

Depending on the availability of the water head, HPPs can be subdivided into low-head (less than 30 m), medium-head (30–300 m), and high-head hydroelectric plants (1,000 m and above). Low-head HPPs can be further subdivided into small, mini, and micro-head hydropower plants.

10.1.2.3 Classification by Nature of Load

Classification by nature of load is as follows.

Base Load Plants

A base load power plant is one that provides a steady flow of power regardless of total power demand by the grid. These plants run at all times throughout the year, except in the case of repairs or scheduled maintenance.

Peak Load Plants

Due to their operational and economic properties, peak load plants are generate electricity during peak load periods. Gas turbines, storage and pumped storage power plants are examples of peak load power plants. The efficiency of such plants is around 60–70%.

10.1.3 Importance of Location on Use Factor of Hydropower Plants

Installation of hydropower plants generally starts with the identification of potential locations, followed by a cost-benefit analysis and environmental impact assessment. The task of trying to identify suitable locations in inaccessible areas has often hindered the growth of hydroenergy potential. Thus, GIS and remote sensing are used, as shown by Ghadimi et al. (2011), Cyr et al. (2011), Yi et al. (2010), Kusre et al. (2010), and Larentis et al. (2010). These tools are generally used to determine topographical parameters like head and storage capacity. Image processing is normally performed on satellite imagery because these tools help to extract information about the possible geophysical properties of a location without requiring a visit to the proposed site, which may be located in an inaccessible area. Such visits also incur substantial outlays for logistical support.

Some studies have also used hydrologic models like SWAT or regression equations to determine flow through proposed locations (Cyr et al. 2011; Kusre et al. 2010).

With regard to the parameters used to identify the best option, most studies considered flow and head (Dudhani et al. 2006; Rojanamon et al. 2009; Supriyaslip et al. 2009; Kusre et al. 2010; Yi et al. 2010; Cyr et al. 2011; Fang and Deng 2011). Some scientists, though they are few in number, explicitly included electrical factors like installed capacity, distance from transmission lines, load requirement, etc. Very few studies considered the social acceptance of hydropower projects (Fang and Deng 2011; Supriyaslip et al. 2009; Rojanamon et al. 2009; Nunes and Genta 1996). Environmental parameters like land use and potential pollution were considered in most of the studies, but use of the parameter in decision making was different in different studies. For example, Rojanamon et al. (2009) tried to select locations by ranking them according to their environmental and ecological sensitivity. They also considered social acceptance at the time the final decision was made. Minimum ecological flow, land use, sedimentation, and river bank erosion were considered as environmental factors in the selection of locations for a hydropower plant. Safety of the area, social conflict, legal aspects (Supriyasilp et al. 2009), and overall social acceptance (Rojanamon et al. 2009) were generally considered social factors. Most of the studies collected the necessary data from onsite surveying, focus group discussions, and review of the historical case studies.

In the final step of the decision-making process, an index was created giving weight to the different factors according to their importance in the development of hydroelectric power plants. The importance of the different factors was generally determined on the basis of the local experience and knowledge acquired from discussions with expert personnel.

After the weighting was set, an objective function was calculated using the values of the different factors and their weighting. According to the values of the objective function, suitable locations were identified for hydropower generation. Most studies on the selection of suitable locations for HPPs have used this method.

10.1.4 Cluster Analysis Algorithms

Cluster analysis, or clustering, is the task of assigning a set of objects to groups (called clusters) so that objects in the same cluster are more similar (in one sense or another) to each other than to those in other clusters. Cluster analysis, which is also referred to as data segmentation, has a variety of goals, all of which relate to grouping or segmenting a collection of objects (also called observations, individuals, cases, or data rows) into subsets, or "clusters," such that those within each cluster are more closely related to one another than to objects assigned to different clusters.

Central to all of the goals of cluster analysis is the notion of the degree of similarity (or dissimilarity) between the individual objects being clustered. There are two major methods of clustering – hierarchical clustering and k-means clustering (Table 10.1).

10.1.4.1 Hierarchical Clustering

In hierarchical clustering, data are not partitioned into a particular cluster in a single step. Instead, a series of partitions takes place, which may run from a single cluster containing all objects to n clusters, each containing a single object.

Hierarchical clustering is subdivided into *agglomerative* methods, which proceed by series of fusions of the n objects into groups, and *divisive* methods, which separate n objects into successively finer groupings.

10.1.4.2 K-Means Clustering

A nonhierarchical approach to forming good clusters is to specify a desired number of clusters, say k, then assign each case (object) to one of k clusters so as to minimize the measure of dispersion within the clusters. A very common measure is the sum of distances or sum of squared Euclidean distances from the mean of each cluster. The problem can be set up as an integer programming problem, but because

Table 10.1

Reference	Location	Type of HPP	Tools used	Engineering factors	Environmental factors	Socio-economic factors
Ghadimi et al. (2011)	Lorestan province in Iran	Microhydro power	GIS and local expert opinion	Flow rate and head; existing density of river and canal network	None	Only economic parameters included
Fang and Deng (2011)	Southwestern China	Cascade hydropower plant	Literature review, case studies to develop three reference scales	Per-unit drop of water level and per-unit change in flow (three scales are developed based on these two and minimum ecological flow)	Minimum ecological flow	Social status of different sections of river was considered
Cyr et al. (2011)	New Brunswick, Canada	Small conventional as well as run of river	Digital elevation models of study area to determine elevation and regression model to estimate stream flow	Stream flow, head, and penstock length	None	None
Yi et al. (2010)	Geum River basin, Korea	Small	Geospatial information system	Head, storage capacity, runoff-contributing area	Environmental assessment map was used to extract information related to environment and ecology	None
Kusre et al. (2010)	Kopili River basin in Assam, India	Micro (<0.5 MW)	Geospatial tools and SWAT hydrologic model	Weather and discharge	Soil and land use	None

(continued)

Table 10.1 (continued)

Reference	Location	Type of HPP	Tools used	Engineering factors	Environmental factors	Socio-economic factors
Larentis et al. (2010)	Brazil	Run of river and storage SHP	Remote sensing, available stream flow data, and GIS-based Hydro Spot software	Flow regulation and river basin potential for power generation	None	None
Supriyasilp et al. (2009)	Ping River basin, Thailand	Small (approx. 100 KW)	Data collection	Electrical criteria like installed capacity, annual energy production, length of transmission line, and firm load supply possible; general engineering criteria like head and flow	Flow pattern, amount of flow, loss of habitat, land use, collapse of river bank, and sedimentation	Safety in location, social conflict, water resource issues, land use issues, legal aspects, and infrastructure available
Rojanamon et al. (2009)	Upper Nan River basin, Thailand	Small run-of-river	GIS, questionnaire survey, group discussion	Average annual flow and average annual head	Geomorphological variations and presence of forests and other plantations	Opinion survey followed by focus group discussion
Dudhani et al. (2006)	India	Small, mini, and Micro	GIS and remote sensing (image segmentation based on intensity of RGB pixels)	Geophysical properties for determination of flow	None	None
Nunes and Genta (1996)	Uruguay	Small(1–5 MW), mini < (1 MW), and micro (<100 kW)	New assessment methodology, calculation and simulation tools were developed	Topographic conditions evaluated for estimating amount of power	None	Average demand for power

solving integer programs with a large number of variables is time consuming, clusters are often computed using a fast, heuristic method that generally produces good (but not necessarily optimal) solutions. The k-means algorithm is one such method.

Along with these two major clusterization algorithms, a few other specialized concepts have also been used to cluster data sets. Principal component analysis, fuzzy logic, and neural network for clusterization are also applied to classify data sets in an unsupervised manner.

10.1.4.3 Principal Component Analysis

In data mining, one often encounters situations where there are a large number of variables in a database. In such situations it is very likely that subsets of variables will be highly correlated with each other. The accuracy and reliability of a classification or prediction model will suffer if one includes highly correlated variables or variables that are unrelated to the outcome of interest. Superfluous variables can increase the data-collection and data-processing costs of deploying a model on a large database. The dimensionality of a model is the number of independent or input variables used by the model. One of the key steps in data mining is finding ways to reduce dimensionality without sacrificing accuracy.

Performance of clusterization depends largely on the characteristics of the data to be classified. There is no single classifier that works best on all problems (a phenomenon that may be explained by the no-free-lunch theorem). Various empirical tests have been performed to compare classifier performance and to find the characteristics of data that determine classifier performance. Determining a suitable classifier for a given problem is, however, still more an art than a science.

10.1.5 Objective and Scope

The identification of an optimal site for an HPP is complex and involves rigorous collection of data, field surveys, and impact analysis. That is why selection parameters are first generalized in such a way that decision making can be as easy as possible. Both traditional and nonconventional methods of site selection mainly involve prioritization of parameters, giving more weight to and ultimately making decisions based on the output value from a weighted-average formula or an activation function (Fig. 10.2).

Many studies have also considered the opinions of people affected by HPPs. The value of a given weight is defined by relevant experts and survey results. Such weighting generally ignores regional characteristics and is decided based on the experience gained from previous works. But overdependence on experience and ignorance of local features may result in an erroneous estimate of storage capacity for the proposed hydraulic structures, turbines, and generators. In this regard, the present study will propose two clusterization algorithms for selection of the most suitable sites for an HPP based on selected parameters.

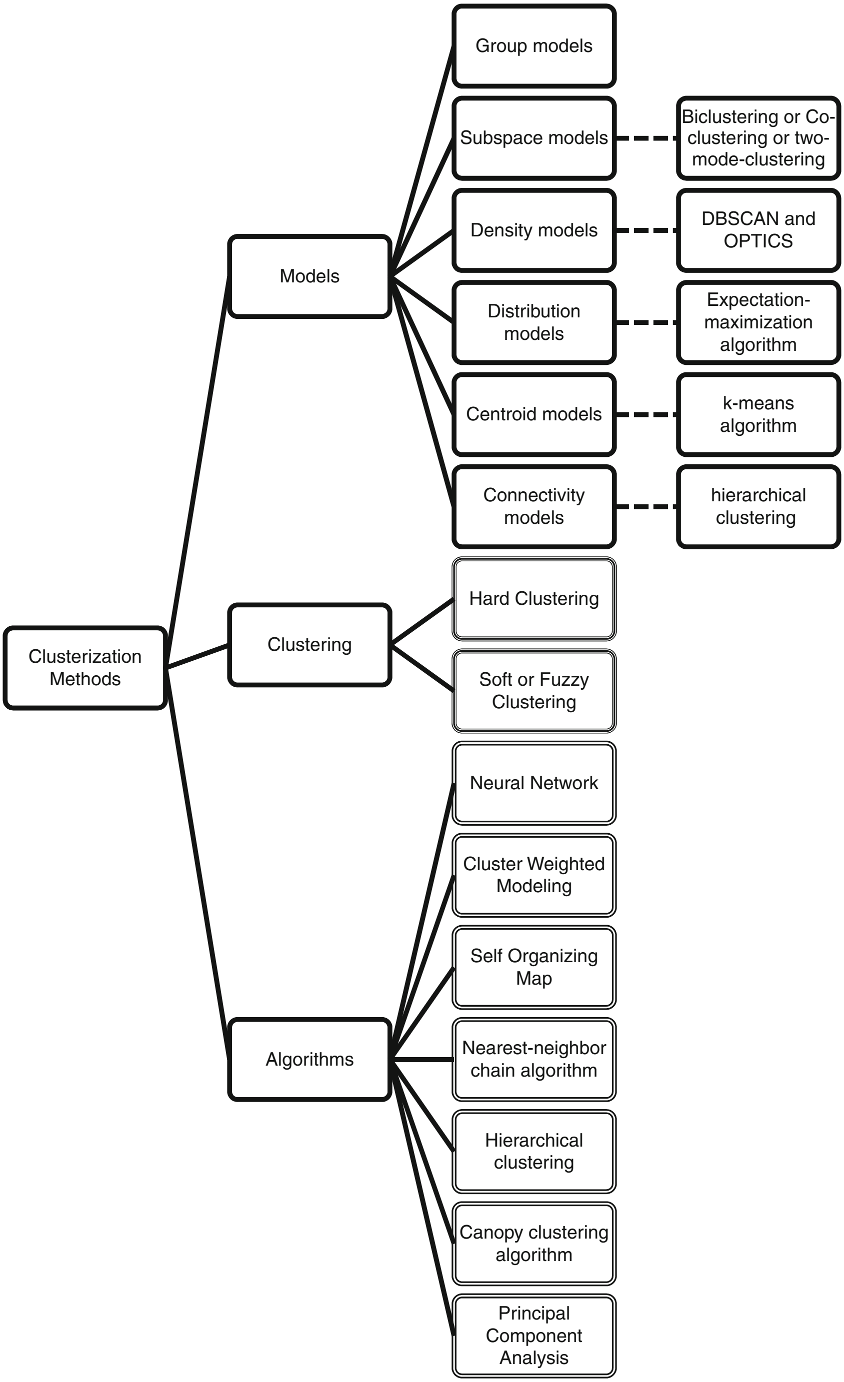

Fig. 10.2 Clusterization models and clustering methods

The main objective of the present study is to analyze the potential of automated clusterization algorithms by a bat algorithm and fuzzy logic to identify the optimal site for an SHP plant. The objective of identifying a suitable methodology for site selection is accomplished simultaneously.

10.1.6 Proposed Methodology

Some studies have also used hydrologic models like SWAT or regression equations to determine flow through proposed locations (Cyr et al. 2011; Kusre et al. 2010).

With regard to the parameters used to identify the best option, most studies considered flow and head (Dudhani et al. 2006; Rojanamon et al. 2009; Supriyaslip et al. 2009; Kusre et al. 2010; Yi et al. 2010; Cyr et al. 2011; Fang and Deng 2011). Some scientists, though they are few in number, explicitly included electrical factors like installed capacity, distance from transmission lines, load requirement, etc. Very few studies considered the social acceptance of hydropower projects (Fang and Deng 2011; Supriyaslip et al. 2009; Rojanamon et al. 2009; Nunes and Genta 1996). Environmental parameters like land use and potential pollution were considered in most of the studies, but use of the parameter in decision making was different in different studies. For example, Rojanamon et al. (2009) tried to select locations by ranking them according to their environmental and ecological sensitivity. They also considered social acceptance at the time the final decision was made. Minimum ecological flow, land use, sedimentation, and river bank erosion were considered as environmental factors in the selection of locations for a HPP. The safety of the area, social conflict, legal aspects (Supriyasilp et al. 2009), and overall social acceptance (Rojanamon et al. 2009) were generally considered social factors. Most of the studies collected the necessary data from onsite surveying, focus group discussions, and review of the historical case studies.

In the final step of the decision-making process, an index was created giving weight to the different factors according to their importance in the development of hydroelectric power plants. The importance of the different factors was generally determined on the basis of the local experience and knowledge acquired from discussions with expert personnel.

In this regard the present study tries to propose a new methodology for classifying the probable locations of HPPs on a river where dependence on expert opinion was avoided by the introduction of automatic clusterization procedures. The most ideal location for an HPP is selected based on the classification results. Classification will be performed by both bat and fuzzy clusterization methods. The results from both clusterization algorithms will be compared based on performance metrics like sensitivity, specificity, precision, and kappa index of agreement.

10.1.7 Bat Clusterization

A microbats is a type of bat that uses echo location to identify a potential food source. Microbats fly around randomly at varying speeds, emitting auditory signals from their mouths with varying loudness. When they find prey, their velocity as they fly toward the location of the prey increases along with the frequency and loudness of their pulse. The change in pulse rate is a signal to other bats regarding the potential food source and invites them to the spot.

In practical problem solving, each food source location is compared with the location of the optimal solution and the rate of convergence toward the solution increases when the fitness functions that are used to analyze the optimality of the solution acquire higher values. Both the frequency and loudness of the pulse then increases, which helps the search algorithm to possibly identify the optimal solution to the given multisolution problem.

The bat algorithm is also a nature-inspired metaheuristic identified by Yang only in 2010.

Because the algorithm is new, few applications using it are available in the scientific literature.

10.2 Methodology

10.2.1 Selection of Factors

In the selection of factors, first a thorough survey of available studies was carried out. Based on the literature survey the most important factors were selected and grouped into four categories. The following section describes the selected factors and the justification for their selection in identifying the optimal location for installing an SHP plant. The categories are as follows:

1. Hydrologic and geophysical factors
2. Environmental factors
3. Socioeconomic factors

10.2.1.1 Hydrologic and Geophysical Factors

Average Change in Flow

The average flow of a river channel is one of the most important factors in the selection of ideal locations for SHP plants or HPPs. Average flow, or Q, was included as a selection parameter in most earlier investigations. In the present study the average flow was calculated using rainfall (P) and evapotranspiration (ET), along with a loss coefficient (L) that will be described in a later section. Equation 10.1 is used to estimate the maximum possible change in flow per month. After the change in flow is calculated for each month the probability of each flow is estimated to draw a flow duration curve for that location:

$$Q = \langle P - \mathrm{ET} \rangle \times L \tag{10.1}$$

Average Change in Net Head

According to various studies, net head is also included as a factor along with average flow and storage capacity. In this study the average head is represented as the change in net head and is estimated from the difference between upstream and downstream water elevation with respect to the considered location:

$$H = \left(H_{\mathrm{u}} - H_{\mathrm{d}}\right), \tag{10.2}$$

where H is the change in head and H_{u} and H_{d} represent the head upstream and downstream, respectively. Like the previous factor, the change in head was calculated for each month and the average change in head was calculated.

Soil Strength

Soil strength was determined using porosity and soil type, where porosity is inversely proportional to the strength of the soil and the soil type is derived in such way that it becomes directly proportional to the strength of the soil. Equation 10.3 represents the soil strength:

$$s = f\left(\frac{\mathrm{ST}}{p}\right), \tag{10.3}$$

where s is the soil strength, ST the soil type, and p the unit less the porosity value.

Slope

The slope of the location is also estimated. The slope is directly proportional to the flow velocity, and a high velocity will always increase the suitability of a location for installing an HPP. In this study, the slope is calculated using the elevation difference between the maximum and minimum elevation divided by the distance between them.

10.2.1.2 Environmental Factors

Land Use and Land Cover or Loss Coefficient (L_c)

According to the environmental policies of many countries, the removal of forest cover is legal as long as adequate replacement is provided. Thus, HPPs are generally not installed in regions with large concentrations of forests. Again, the distance from a forest dictated whether the profit from the HPP could compensate the displacements of forest and the dependent inhabitants. Forests provide shelter to wildlife and livelihoods to the people living there. If forest cover is severely depleted due to the installation of an HPP and if the resulting gain from the HPP is less than the benefits provided by forest products, then the region is not recommended. In the present study, forest cover was determined using satellite imagery and image processing software like FreeView. The images of the locations were classified and then color for both sparse and dense forest cover was identified. Pixel values at 50 different points ($p_1, p_2, p_3 \cdots p_{50}$) within the same land was first identified and then the area covered by those pixels were estimated using the following procedure.

If the number of pixels with p_n values was C_n, and if the total number of pixels in the image was found to be C_T and the area of the image was A, then the area covered by pixels with a value p_n could be estimated by (where $n = 1$–50):

$$\int_{\text{n=1}}^{50} dA_{p_n} = \int_{\text{n=1}}^{50} \left\{ \frac{dC_n}{C_T} \right\} \times A \qquad (10.4)$$

The total area of that land feature was estimated by adding the areas of all 50 pixels. The areas of other land features were calculated in a similar manner. If some pixels overlapped, i.e., same pixel is identified to represent two type of land features, then the area of the overlapping pixel is first determined. Then this area is removed from the total area of the image while calculating the extents of individual land use. The distance from the river was measured using a measurement tool available in GIS packages like MapWindow GIS.

This new method was used to estimate the area of:

1. Vegetation,
2. Irrigation fields,
3. Bodies of water,
4. Barren land.

The infiltration or retention capacity of all the above types of landuse is relatively higher than that of the other land use features like pavement, road, or impervious structures.

That is why calculation of the LULC coefficient of a region entails estimating the ratio of the impervious area to the total area. The area of impervious structures are calculated by deducting the sum total of the pervious areas from the total area.

Frequency of Fish Navigation

One of the major drawbacks of HPPs is that they prevent fish populations from navigating freely. Fish navigate in search of food and to locate a suitable location for spawning. Both of these activities are hindered if the path of navigation is blocked by an HPP. That is why frequency of fish navigation varies inversely to the suitability of HPP installations.

Water Quality

An index similar to the NSA water quality index is calculated to represent the overall quality of river water. But instead of parameters related to waste water; quality parameters like TDS, TSS, and pH are used, all of which represent the overall suitability of the water of a river for prime mover. Water with a high concentration of salinity will corrode the blades of a turbine. Again, high TDS or TSS concentrations will represent a high carrying capacity of a river, which generally causes a large amount of sedimentation, which is not beneficial for the turbines of the HPP.

10.2.1.3 Socioeconomic Factors

Average Energy Potential

The energy potential of a river network can be calculated from the average flow and net head. The power generated is calculated with the help of a power equation.

Potential Profit

The profit from an HPP is generally calculated after the cost of installation is recovered. The main income of any HPP is from selling units of power produced at the plant. The expenditures from an HPP include the cost involved in installation, logistics and transportation, land acquisition, labor, relocation of affected population, purchasing of auxiliary power, and other maintenance costs. It was found that a minimum of 5 years is required to recover the installation costs of an HPP depending on the demand and unit price of the supplying region. After that, profit becomes a function of the available potential energy in the stream and variation in selling price, which is controlled by market forces.

Distance from Grid

The distance from the grid is inversely proportional to the suitability of installing HPPs. The greater the distance, the less suitable the location for an HPP. As resistance is directly proportional to the length of a conductor, a long conductor will have higher resistance. An increase in the resistance will also increase the loss of electrical energy. Also, a longer distance will require longer transmission wires, which will increase the overall cost of the power plant. Although few studies include this parameter, the importance of distance on the loss of electrical energy is well documented.

Distance from Consumers

Similarly, the distance from consumers also varies inversely with the suitability of a location for an HPP. The greater the distance, the greater the loss and costs of conducting electricity to the target consumers.

10.2.2 Development of Clusterization Algorithm

In the present investigation, instead of applying conventional clustering methodologies, the novel concepts of fuzzy logic and bat algorithm were used to achieve the study objective.

10.2.2.1 Application of Fuzzy Clusterization

At first, a weighted average of all the factors according to their magnitude was developed where the weights for each of the factors were estimated with the help of fuzzy logic and a bat algorithm.

Table 10.2 describes the weighting for the factors as determined by fuzzy logic.

10.2.2.2 Application of Bat Algorithm

A search optimization algorithm inspired by the echo-location abilities of microbats was developed by Xin-She Yang in 2010. This bat algorithm mimics the method adopted by microbats for locating prey. The method involves varying the rates of pulse emission and loudness based on nearness to prey.

Each bat flies randomly searching for its prey with varying frequency and loudness of pulse emission. When it locates prey, it changes the frequency and loudness of pulse-rate emission. The nearer it comes to its prospective prey, the emission rate from the bat becomes quicker and the pulse becomes louder.

Table 10.2 Rating assigned to some factors with respect to other factors by degree of importance in selection mechanism

	Average change in flow	Average change in net head	Soil strength	Slope	L_c	Fish navigation	Water quality	Average energy potential	Potential profit	Distance from consumers	Distance from grid	Weighting
Average of change in flow		3	2	2	2	1	1	3	3	2	2	0.66
Average change in net head	3		2	2	2	1	1	3	3	2	2	0.66
Soil strength	4	4		4	2	3	3	4	4	4	4	0.50
Slope	4	4	2		3	3	3	4	4	3	3	0.50
L_c	4	4	4	3		3	3	4	3	3	3	0.25
Fish navigation	5	5	3	3	3		2	4	4	2	2	0.6
Water quality	5	5	3	3	3	4		4	4	3	3	0.40
Average energy potential	3	3	2	2	2	2	2		3	2	2	0.33
Potential profit	3	3	2	2	3	2	2	3		2	2	0.33
Distance from consumers	4	4	2	3	3	4	3	4	4		4	0.50
Distance from grid	4	4	2	3	3	4	3	4	4	2		0.50

When the food foraging behavior of bats is applied to solve a problem, the location of a prospective solution is compared to the location of prey. A random search for food by a bat is comparable to random numbers. The pulse rate of emission is represented by *r*, and A_i denotes the magnitude. The higher the rate and magnitude of a pulse, the closer the location of the solution.

In the present investigation, the bat algorithm was applied to select the most suitable location for an SHP plant.

Definition of Good and Bad Location for Availability of Food

To mimic the bat algorithm, first the good and bad locations with respect to availability of food were defined and rated. A high magnitude of factors and low magnitude of factors that respectively increase and decrease the chance of selection of a site for installation of an SHP plant were rated highly, i.e., the chances of finding food at these locations are higher.

Assignment of Randomly Flying Bats to Locations

In the next step, the bats were assigned random numbers, which were multiplied by the rating of the factors to come up with a weighted average. This average was calculated for all the available locations and then normalized. An increase in the random number will increase the chances of selection if the factor is rated as good, and vice versa.

Here randomly flying bats are comparable to the random number that is based on the ratings of the factor or quality of the location increases chance of selection.

Food Spotting

This normalized weighted average can be compared with the pulse rate of microbats whose rate and magnitude increase with the spotting of a food source. The higher the pulse rate, the more reliable is the location of the food source. The weighting at which a location has its maximum weighted average will be the most suitable location for installation of an HPP.

Not only would the attainment of the maximum weighting value make the location optimal, but the rate at which it attains optimality would actually determine its electability. Like the bat, this increases its pulse rate when it finds a location where food is most likely to be present.

This three-stage food-foraging activity was thus mimicked in the present study to identify the most suitable location from among the sample locations available for hydropower generation.

10.3 Results and Discussion

Table 10.3 presents the results of the clusterization and identification efficiency of the algorithms for spotting the best location out of the available nine samples. Location 1 was the ideal one and both algorithms were able to identify it as such. But where fuzzy logic took one iteration only to identify the best location, the bat algorithm took six iterations to achieve the objective.

However, the bat algorithm turned out to be more sensitive and more precise than fuzzy logic as it clearly delineated the optimal solution.

Table 10.3 shows the normalized value of the weighted average as determined from the weighting estimated from the fuzzy and bat algorithms. The respective clusters are also shown in the last column of the table. The number of iterations needed to identify the optimal location was one for the fuzzy and six for the bat algorithm, whereas the sensitivity of selection as represented by the magnitude of the normalized weighted average was clearly higher in the case of the bat algorithm (1.000) than with the fuzzy algorithm (0.894).

Thus, if computational power is not a constraint, then bat-based clusterization can be used to identify the optimal location for an HPP; otherwise, a fuzzy algorithm may be preferred.

Table 10.4 shows the weighting determined by both algorithms in estimating the weighted average of the factors by which the optimal location could be identified.

10.4 Conclusion

The present investigation tried to identify a suitable location for installation of an SHP plant with the help of two algorithms: fuzzy and bat. The potential of both in clusterizing decision variables was also analyzed. It was found that if computational power is not a constraint, then the bat algorithm is better for clusterization than

Table 10.3 Normalized weighted average of factors with respect to weights determined by fuzzy and bat algorithms and corresponding clusters assigned to locations

Location	Normalized fuzzy weighted average	Normalized bat weighted average	Clusters
1	*0.894*	*1.000*	*9*
2	0.790	0.875	8
3	0.690	0.750	7
4	0.593	0.625	6
5	0.500	0.500	5
6	0.411	0.375	4
7	0.324	0.250	3
8	0.241	0.125	2
9	0.160	0	1

Table 10.4 Weighting of factors as estimated using fuzzy and bat algorithms

Factors	Fuzzy	Bat
Average of change in flow	0.6600	0.6506
Average change in net head	0.6600	0.8546
Soil strength	0.5000	0.6126
Slope	0.5000	0.3214
L_c	0.2500	0.7673
Fish navigation	0.6000	0.6381
Water quality	0.4000	0.4656
Average energy potential	0.3300	0.4960
Potential profit	0.3300	0.0531
Distance from consumers	0.5000	0.9008
Distance from grid	0.5000	0.6508

fuzzy-based clusterization. The optimal solution of the present study was already known but was included in the sample population so that the potential of both algorithms could be verified. The results show that, although both algorithms successfully identified the optimal solution, the sensitivity with which the bat algorithm identified the solution surpassed the sensitivity shown by fuzzy clusterization. But bat's requirement for a higher number of iteration can create problems when computational capacity is not high enough to carry out large numbers of iterations.

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