Chapter 3
Tradeoff Analysis Between Rainfall and Load Factor of a Small-Scale Hydropower Plant by Particle Swarm Optimization

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Abstract Hydropower is claimed to be one of the least expensive but most reliable sources of renewable energy. The frequency of power generation depends directly on the flow of water on which the power production facility has been constructed. The flow of water depends on the upstream rainfall, which contributes to the surface runoff to create the flow in the channel which rotates the turbine for production of electricity. The utilization factor of a hydropower plant (HPP) is defined as the ratio between the energy actually produced to the energy production capacity of the hydropower plant (HPP). It is synonymous with load factor if the capacity of the HPP and the maximum energy produced become equal. The present study will aim to identify the optimal zones where minimum rainfall and maximum utilization can be achieved by employing particle swarm optimization within the known constraints of small scale hydropower plant. The result of the study will highlight the adjustments required to be followed in the hydropower plants in generating optimal power output even in the days of scarce rainfall.

Keywords Small-scale hydropower • Particle swarm optimization • Tradeoff

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3.1   Introduction

The utilization factor is the ratio of the maximum load on a power plant to the rated plant capacity, whereas (electrical) load factor can be defined as the average power divided by the peak power over a period of time. If the peak power is equal to the rated plant capacity, then the utilization factor and load factor will be equal.

In the case of a hydropower plant (HPP), the utilization factor depends mainly on the amount of upstream and local rainfall which is the driving force of any hydropower plant. The rated plant capacity will depend on the maximum possible flow that was observed in the flow duration curve of the river on which the power plant was developed. The maximum load on the other hand will depend upon the demand of power from the plant.

The demand for power depends on various factors where change in rainfall is one of the main parameters for which a change in production capacity is observed. During summer, the demand for electricity is high because of the continuous requirement for fans, air-conditioners, and other cooling devices. But during winter, the demand for power is reduced because requirements for electricity diminish. The only major requirement in terms of energy use during this time of year is for running the air-heating devices.

In the case of HPPs, the generation of power also varies with regional climate patterns because the power production capacity of any HPP depends mainly on the velocity of flow, which again is a function of rainfall and head difference. And as demand for power varies with climate also, the average load will vary with change in weather pattern.

That is why, in summary, it can be stated that both the load factor and utilization factor are functions of rainfall. If power demand and rainfall both changes, then the zone in which the load factor reaches its maximum will also change. This study aims to identify the status of the power demand and rainfall when the load factor will become nearly equal to utilization factor. The study used the inherrent searching capability of particle swarm optimization (PSO) to accomplish this objective. There are various types of hydropower plant and this zone where utilization and load factor will become equal also varies with the type of hydropower plant. In the present investigation te small scale hydropower plants are only considered. The next section explains the classification of HPP.

3.1.1   Classification of Hydropower Plants

Based on water head, HPPs can be classified into three types: low-head, medium-head, and high-head HPPs.

3.1.1.1   Low-Head Hydroelectric Power Plants

Low-head HPPs can be defined as power plants where the available water head is less than 30 m. Most of the time, due to the very short head of such power plants,

dams are not constructed; instead, a weir is used and the inherent flow of water in the canal/river is used to generate electricity. The low-head types of HPPs are of the nonstorage type and generate electricity only when sufficient flow of water is available. Thus, their relationship to rainfall is directly proportional, i.e., they can produce electricity only during particular seasons like the monsoon season, when abundant flow of water is available. Because the available head of water is directly proportional to electricity production capacity of any HPP, the power-producing capacity or utilization factor of such plants is very low due to lack of reliability and stability in the availability of kinetic energy in the canal/river.

3.1.1.2 Medium-Head Hydroelectric Power Plants

HPPs having a working head of water more than 30 m but less than 300 m are referred to as medium-head HPPs. These HPPs have their own storage systems and are usually developed in mountainous or hilly regions so that the advantage of the height difference can be used for power generation.

3.1.1.3 High-Head Hydroelectric Power Plants

High-head HPPs have a head of water varying from 300 to 1,000 m. Large reservoirs of water in dams that can store water at very high heads are developed, and turbines are connected through penstock so that the water from the dam can be used to rotate it and produce huge amount of power from the generators. Water is mainly stored during the rainy season and can be used in the lean season. Thus, high-head HPPs can generate electricity throughout the year. The total height of the dam will be a function of a number of factors like quantity of available water, power to be generated, surrounding area, natural ecosystem, etc.

   In the present study the optimal points were identified only for the low-head HPP that varies directly with rainfall.

3.1.2 Impact of Climate Change on Hydropower Plants

The production of greenhouse gases from the domestic and industrial sectors has increased the average temperature of the planet. Due to this global warming phenomenon rainfall patterns have apparently changed in many places around the world. As rainfall is directly related to the generation of hydropower, the effect of warming will hit these plants as well. Thus, it has been asserted that the relationship between the load factor and rainfall will become a vital concern for the engineers in designing the HPPs.

   An increase in temperature will also increase the average load. Thus, the load factor will also change by the change in the climate.

3.1.3   Objective and Scope

The objective of the present study is to determine the tradeoff zones between rainfall, power demand, and load factor. The optimal zones, i.e., minimum rainfall but maximum utilization, will be identified using particle swarm optimization.

These zones can inform engineers about the optimal values of independent variables and highlight the feasibility of a project using the number and magnitude of tradeoff zones.

3.1.4   Brief Methodology

The rainfall data of a low-head river flowing through the northeastern states of India are first collected on a per-month basis. The power demand per month from the adjacent areas of the river is estimated from governmental sources. The discharge of water through the river is estimated from the water balance equation, and the power equation is used for estimation of power production.

After rainfall, demand, and power production are derived, tradeoff zones was generated and identified by the utilization of PSO.

3.2   Particle Swarm Optimization

PSO (Eberhart and Kenedy, 1995) is a population-based search algorithm that follows the behavior of flocks of birds or schools of fish. In this algorithm, random particles are considered as the solution to a given problem space. Each of the particles is a probable solution to the given problems. It gradually converges to the optimal solution based on two criteria:

1. Local best
2. Global best

The iteration starts by selecting random positions for the particles. Each particle has an objective to converge toward the optimal solution in the search domain. The velocity of the particle is updated in the following manner:

$$x_{t+1} = x_t + V_{t+1} \tag{3.1}$$

where

$$V_{t+1} = V_t + c_1 x \text{rand}(0,1) \times (V_{\text{lb}} - v_t) + c_2 x \text{rand}(0,1) \times (V_{\text{gb}} - V_t) \tag{3.2}$$

V_{t+1} = new velocity of the particle as it converges toward the optimal solution; V_t = old velocity acquired by the particle in the previous iteration; x_{t+1} = new position; x_t = old position attained after the last iteration; c_1 and c_2 = learning factors

and random functions that generate random numbers between 0 and 1; V_{lb} = velocity attained for optimal value of fitness function when compared within the old and new positions; and V_{gb} = velocity obtained for the best fitness function achieved until the present iteration. The previous velocity can be updated at each iteration based on the value of the fitness function attained after each iteration, but the value of the latter is generally updated once a better output of the fitness function is achieved.

PSO is similar to many evolutionary computation techniques such as genetic algorithms (GAs). But unlike GAs, the efficiency of PSO does not depend on evolutionary parameters like crossover and mutations.

The simplicity in PSO's application and the need to adjust just a few parameters have made PSO a sought-after iteration technique for optimization problems. PSO has been successfully applied in many areas: engineering design (Feng et al. 2010), multiobjective optimization (Mousa et al. 2012), multiobjective planning (Sahoo et al. 2012), artificial neural network training (Chau 2006) and topology selection of neural networks (Mingo et al. 2012), fuzzy systems (Zhao et al. 2010), parameter estimation (Wang et al. 2011), parameter selection (Parsopoulos and Vrahatis 2007), data clustering (Tsai and Kao 2011), and solving high-dimensional problems (Jia et al. 2011).

Many new variants of PSO are also being developed to improve the accuracy and reliability of the algorithm including discrete PSO, constricted constraints, barebones PSO (Zhang et al. 2012), pooled-neighbor swarm optimization (Guo and Zhao 2006), chaotic multihybrid (Mukhopadhyay and Banerjee 2012), hybrid PSO (Shelokar et al. 2007) and chaotic PSO (Khajehzadeh et al. 2011), particle visual modeling analysis considering the degree of particle distribution and dimensional distance (Zhao et al. 2009), grammatical PSO (Lopez et al. 2012), multiswarm cooperative particle swarm optimizer (Zhang et al. 2011), perturbed PSO (involving linear algorithms for position updates to maintain the diversity of the generated data and prevent premature convergence) (Xinchao 2010), and fully informed PSO (Mendes et al. 2004).

To date, there are nearly 7,209 articles and approximately 3,963 book chapters published in various reputable international journals and books about different applications of PSO in practical problem solving.

3.3   Necessity of Hydropower Plans

Power is one of the most essential inputs for sustaining the economic development of a country, but it also invites degradation of the environment and increases in greenhouse gases, which are the main culprit in climate change. "The inevitable increase in the use of fossil fuels to keep pace with the economic growth has associated side effects of threat to energy security of the country and environmental degradation through climate change" (Anonymous). The ever-growing world population and economic development have put pressure on existing

resources for power generation. According to the latest reports, the size of the world economy will increase at a rate of 3–5 times by the year 2050 and by 10–15 times by the year 2100 with respect to the present economy. In contrast, the energy requirements of the world will increase 1.5-to 3-fold by 2050 and 2-to 5-fold by 2100.

At present the primary energy consumption of the world is dominated by fossil fuels like oil (36%), natural gas (21%), and coal (24%). Biomass (9%), nuclear fuels (6%), and large hydro and other renewable energy sources (2%) complete the global power consumption scenario. The dependency on fossil fuels has caused several detrimental effects on the environment and ecological balance. Due to the combustion of such finite sources of energy greenhouse gases like sulfur, nitrogen oxides, carbon monoxide, and suspended particulate matter are abundantly present in the atmosphere causing global warming and concomitant climate change. Ozone layer depletion, land degradation, air and water pollution, sea level rise, and loss of biodiversity are other negative impacts of using fossil fuels.

The global consumption of primary energy is increasing at a rate of 2% per year (68 J/capita/year and 1.6 tonnes of oil equivalent/capita). The three primary energy sources are found to have 0.4, 2.3, 1.5, and 0.9% ratio of supply to reserve respectively for coal, oil, natural gas, and total energy sources. Although a minor part of the available reserves are used for consumption, still not all reserves have a 100% utilization factor (Nakicenovic 2012 and HDR 1998).

3.3.1   Global Scenario of Renewable Energy

Energy that can be naturally replenished is referred as renewable energy. The major sources of such energy are sunlight, wind, rain, tides, and geothermal heat. Only 16% of global final energy consumption comes from renewable sources; this figure was only 13% in 1998. The major share of renewable energy is biomass (10%), followed by 3.4% from hydroelectricity. New renewable (small hydro, modern biomass, wind, solar, geothermal, and biofuels) contributes another 2.8% (REN21 2011a). "The share of renewables in electricity generation is around 19%, with 16% of global electricity coming from hydroelectricity and 3% from new renewables" (REN21 2011a).

The contribution of wind power to global renewable energy generation is 30% annually (REN 2011), and the installed capacity of photovoltaic energy is more than 40 GW (REN 2011). Brazil has the largest renewable energy program in the world, where energy from ethanol provides 19% of the total energy requirements of the country.

Renewable energy sources are environmentally friendly and do not produce greenhouse gases, and, although renewable energy is infinite, the cost of conversion and the uncertainty in its availability earlier discouraged the governments of different countries from opting for such energy sources to satisfy their energy needs. But due to the rapid pace of economic development, the growth in energy demands to sustain this trend, and the damaging impacts of fossil fuel, many countries have opted for

renewable energy. According to the latest reports, small solar PV systems provide electricity to several million households, and micro-hydro configured into mini-grids serves many more. Over 44 million households use biogas made in household-scale digesters for lighting or cooking, and more than 166 million households rely on a new generation of more-efficient biomass cook stoves (REN21 2011b).

In the case of hydropower, at least 50% of the electricity production in 66 countries and at least 90% in 24 countries is supplied from the energy produced from HPPs.

3.3.2 Classification of Hydropower Plants

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

3.3.2.1 Classification with Respect to Quantity of Water

HPPs can be classified based on the amount of water used in the following way:

Runoff River Plants Without Pondage

These kinds of plants do are unable to store water and use water as and when available. That is why such plants are dependent on the rate of flow of water; during the rainy season, a high flow rate may mean that some water is wasted, whereas during low run-off 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 is more useful than a plant 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.

Reservoir Plants

A reservoir plant is one that has a reservoir of such a size as to permit carrying over storage from the wet season to the next dry season. Water is stored behind a dam and is available to the plant with control, 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.

3.3.2.2 Classification by Availability of Water Head

Based on the availability of the water head, an HPP can be subdivided into Low or Small head (less than 30 m) (SSHP), 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 HPPs.

3.3.2.3 Classification with Respect to Nature of Load

Classification according to the 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: these are power plants for electricity generation that, due to their operational and economic properties, are used to cover peak loads. Gas turbines and storage and pumped storage power plants are used as peak load power plants. The efficiency of such plants is approximately 60–70%.

The present investigation selected a small-scale HPP for optimization of load factor using PSO algorithms.

3.4 Methodology

The main objective of the present investigation is to optimize the load factor in such a manner that it attains a value of 1 or close to 1 because at that value the average load and peak demand become equal, which means the power plant can function at an efficiency of nearly 100%.

The variables for the present study are the amount of rainfall and demand for power. The constraints of the study were as follows:

$$\text{Precipitation in the Catchment Area of the SSHP}\,(\text{Rain}) < 2{,}500\ \text{mm}$$
$$\text{Demand for Power}\,(D) < 20\ \text{MW}$$

The objective function is taken as the resulting value of the subtraction of the load factor from one. Minimization of this resulting value will be the optimal output possible from the Small Scale Hydropower Plant (SSHP) of the present study.

PSO is used to generate different values of rainfall and demand for power in a restricted search domain where the upper limit is determined by the constraints imposed on the variables.

C_1 and C_2, the scale factors, are taken as two, and the fitness function is the objective function itself. If its value is lower than for the previous iteration, then the local best is updated; if the value is the lowest of all iterations up to that point, then the global best is updated.
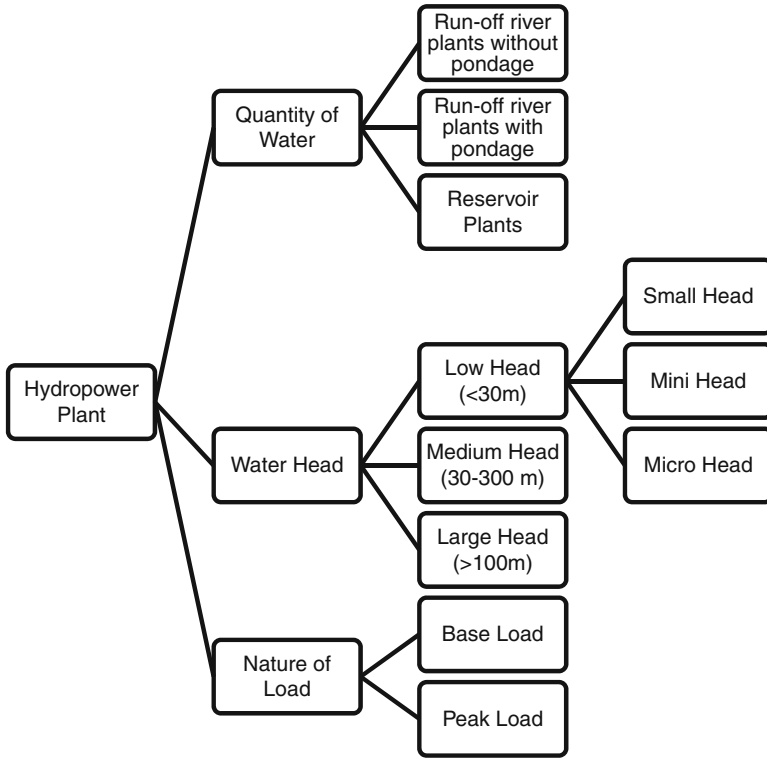
Fig. 3.1 Classification of HPP with respect to different attributes

In this manner 300,000 iterations were performed and the 30 most optimal results were selected from among them. Figure 3.1 depicts the 30 most optimal results of the search and the corresponding normalized values of the variables and objective function L, which was actually derived from

$$L = 1 - (D/P). \tag{3.3}$$

When the difference between the load factor (Eq. 3.3) and unity is at a minimum, the SSHP will operate optimally at that reference point and those conditions of the variables.

To generate the different values for the selected variables of the present optimization study, the positions generated by the PSO are multiplied by the upper limit of the problem domain so that the regenerated swarm of solutions stays inside the required boundaries of the problem space.

The amount of power that can be generated is derived from the water balance and power equation. Demand values are selected with respect to the common magnitude of demand faced by any SSHP in the world, and rainfall limits are derived from the data of rainfall patterns in tropical countries.

3.5   Results and Discussion

PSO was used to adjust the value of the variables within the given upper limit. The value of the rainfall and demand for power was varied 300,000 times, and each time a new load factor was generated. The load factor was compared with unity and the lower the value of the difference, the more optimal the selection. From the 300,000 load factors 100 values per generation were collected. The values were then ranked and the minimum value obtained (Eq. 3.3) was identified and saved to a data matrix. Similarly, for 30 separate iterations, 100 values were collected and ranked in ascending order. The top-ranked objective function was identified and, along with its variable, saved to the same data matrix. The data matrix was normalized and ranked to identify the minimum. The output of this procedure is shown in Fig. 3.2.

For 60%-plus cases the convergence of PSO toward the optimal solution was observed before 50,000 iterations, but for the remaining case the optimal solution

Rain	D	L		
0.28125	0.2813	0.0139		10
0.40625	0.4063	0.0166		14
0.125	0.125	0.1506		31
0.1875	0.1875	0.006		5
0.59375	0.5938	0.0043		3
0.9375	0.9375	0.1065		28
0.0625	0.0625	0.0817		26
0.5	0.5	0.0164		13
0.09375	0.0938	0.0454		22
0.21875	0.2188	0.0341		17
0.4375	0.4375	0.0035		2
0.34375	0.3438	0.0516		23
0.90625	0.9063	0.0768		25
0.53125	0.5313	0.0143		11
0.75	0.75	0.0244		16
0.3125	0.3125	0.0353		18
0.5625	0.5625	0.0184		15
0.96875	0.9688	0.0934		27
0.875	0.875	0.0658		24
0.65625	0.6563	0.0061		6
0.84375	0.8438	0.0399		20
0.8125	0.8125	0.0377		19
0.71875	0.7188	0.0126		9
0.375	0.375	0.0061		7
0.25	0.25	0.1335		30
0.6875	0.6875	0.0046		4
0.625	0.6563	0.0006		1
0.78125	0.7813	0.0155		12
0.46875	0.4688	0.04		21
0.03125	0.0313	0.0112		8
0.15625	0.1563	0.1193		29

Fig. 3.2 Thirty most optimal outputs from 30,000 generations of solutions using PSO (*rain*: rainfall percentile, *D*: demand for power, percentile; *L*: objective function deducting one from load factor; *red columns*: rank of objective function)

was identified after 50,000 iterations and for 10% of the cases it was observed after 90,000 iterations, although the best solution among all the iterations was observed only at the 270,000th iteration.

PSO is known to be a quick convergent, but the present investigation shows that the best solution is obtained only after 90% of considered iterations were completed.

3.6   Conclusion

The present investigation tried to optimize the load factor of a small-scale HPP (10 m head). A PSO algorithm was used to generate data for the variables considering the upper limit imposed on those variables. After the iteration procedure it was found that a rainfall in the 62.5th percentile and a demand in the 65.65th percentile are required for the SSHP to perform at optimal load factor. The study results can be used in the planning of an SSHP during the feasibility analysis phase. Although PSO is considered a fast convergent, according to the present study, it takes more than 90% model time to identify the optimal solution. Determining the reasons for such results is left to future researchers.

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