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Energy Procedia 90 (2016) 107 – 113

Energy Procedia

5th International Conference on Advances in Energy Research, ICAER 2015, 15-17 December 2015, Mumbai, India

Optimization of Renewable Energy Sources in a Microgrid Using Artificial Fish Swarm Algorithm

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Abstract

Advances in microgrid enabling technologies and utilization of Renewable Energy Sources are prompting more and more number of smaller investors to invest in Renewable energy generation and distribution at microgrid level. The increased competition requires the energy producers to offer energy at minimum possible cost to gain the confidence of consumers, which needs efficient methods to schedule the energy generation among the available Renewable Energy Sources. Optimal scheduling of generation is one of the methods used to reduce the cost of generation. Out of many types of algorithms used effectively to solve the problem, evolutionary program techniques are proven and time tested to be one of the best solutions. A stochastic based search algorithm, called Artificial Fish Swarm Algorithm is used in this article to solve the problem of optimal scheduling of energy generation among the available Renewable Energy Sources. The effectiveness of the algorithm is validated by implementing to schedule generation in a microgrid scenario. The results are validated by comparing to an already tested Additive Increase Multiplicative Decrease algorithm.

Peer-review under responsibility of the organizing committee of ICAER 2015

*Keywords:*Optimization;Cost of generation;Generation schedulling;Artificial Fish Swarm Algorithm

1. Introduction

A microgrid is defined as a single controllable system of a cluster of loads and micro sources supplying both power

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Peer-review under responsibility of the organizing committee of ICAER 2015
doi:10.1016/j.egypro.2016.11.175

and heat [1]. Advances in microgrid enabling technologies are augmenting the harness of Renewable Energy Sources (RESs) to meet the ever increasing demand for energy. RESs are becoming prominent alternatives to conventional sources due to developments like improved efficiencies, reduced costs of generators, phenomenal increase in capacity of the generators, improved methods of decreasing the uncertainty of energy availability, subsidised policies of governments etc. The prevailing and recuperating operational conditions of RESs and microgrids are gaining the confidence of more and more number of smaller investors to enter the energy markets at all levels, particularly in generation in microgrids. This offers consumers a wider choice of power producers to purchase power from, but the producers face a strict competition among themselves. The development offers a wider scope for distributed / decentralised generation, which in near future is sure to replace the centralised systems at least partially. For instance, Germany is aiming to meet 25-30% of its total energy requirement from RESs by the end of 2030 [2].

The energy markets, in reality with many smaller power producers, offer a strict competition for the energy producers. Offering energy at a competitive tariff rate is the key to successful business. Methods to evaluate the cost of energy from different sources close to reality and methods of reducing the total cost of generation are pivotal in reducing the cost of generation of energy. One among the effective methods of reducing the cost of generation is optimal scheduling of generation among the available sources. Optimal scheduling has been a complex issue for a long time, inspiring a lot of research in conventional power systems. Uncertainty in demand and power availability of RESs adds to its complexity in microgrid environment. A lot of techniques of linear, non-linear and stochastic nature are reported in literature. A stochastic method is formulated to optimise the cost of electricity and natural gas for buildings in [3]. A linear programming technique, Additive Increase Multiplicative Decrease (AIMD) method, is applied to schedule generation of RESs in a microgrid environment in [4]. Some centralised mixed integer linear formulations are explored by researchers for the problem of RESs scheduling in microgrids [5 &6]. The linear programming techniques stated above have their own limitations in view of optimizing capabilities and in many cases their capacities are outperformed by swarm intelligence based algorithms. A number of swarm intelligence based algorithms are developed and are being developed and the same are successfully demonstrated in optimisation applications. A Dolphin Echolocation Optimization technique is used to schedule generation of RESs in a microgrid in [7]. An improved bat algorithm is used to optimize the size of energy storage device in a microgrid in [8]. The objective of this paper is to formulate an energy management system based on Artificial Fish Swarm Algorithm (AFSA) which schedules generation task among the available RESs to optimise the utility function in a microgrid with uncertainty of power availability.

2. Problem statement

The problem is formulated under surplus generation assumption, i.e., at any given time t, the total power generated by all the available RESs is more than the demand.

$$\sum_{i=1}^{n} p_i(t) > d(t) \tag{1}$$

where $p_i(t)$ is the real power generated by i^{th} RES at time interval t, $d(t)$ is the demand on the system at time interval t. Hence (1) allows the EMS to have a choice from the available RESs for generation and its share of generation (p_i) to the total power generation ($\sum p_i$) to cater the demand $d(t)$ at a given time. The load and the total generation can be balanced by the EMS by many methods like disconnecting of some of the non-preferential loads, supplying from its storage facility or by drawing the balance power required from a utility grid or from a neighbouring microgrid. The additional power requirement met from the inherent storage facility or drawn from the connected utility grid in the later two cases can be modelled as another source being governed by (1). However this problem is not significant here as the problem is formulated under assumption that total power generation always meets the demand at any given time.

Cost of generation is the objective function of interest here and the same is considered for optimization. The commonly accepted cost function for RESs in microgrid literature is the quadratic cost function, which is formulated as [9]

$$\mathrm{C}(p_i) = \alpha . p_i^2 + \beta . p_i + \gamma \tag{2}$$

where C is the currency unit, α, β and γ are the cost coefficients that depend on the technology of the respective RES in terms of currency unit. Though the quadratic equation (2) gives complete picture of cost of generation of any type of unit, it is a common practice to neglect the quadratic term α which introduces non-linearity in optimisation problems and consider only the direct costs. The non-linearity can be removed by neglecting α, as is a common practice in literature. However in this paper, the complete quadratic function is considered for computational purposes.

2.1 Artificial Fish Swarm Algorithm

In water, fishes are found to be distributed around the region where food is available and at the same time like to stay close to the swarm. A fish continuously adjusts its position in a swarm in response to external environment and its own state [8]. The movements of individual fishes in a swarm appear to be random, but in reality it is a highly synchronized movement towards the objective. Fishes stay close to the swarm to protect themselves from predators, maintain safer distances from neighbouring fishes to avoid collisions and continuously search food. These behaviours inspired formulation of new algorithms to solve optimization problems with a fair degree of efficiency. The algorithm uses a local searching behaviour of individual fishes, termed as artificial fishes, to reach the global optimal solution. The random search, swarming, following and preying behaviours of the fishes are adopted in the algorithm for the search. The position of each artificial fish denotes a possible potential solution. The current position x_i can be represented by $X_i = (x_{i1}, x_{i2},... x_{in})$ where i is the number of control variables, n is the number of fishes in the swarm. The food consistency that the artificial fish in position x_i can find is given by $Y_i = f(X_i)$. The new position of the artificial X_i^* is given by

$$X_i^* = X_i + rand\,(\,) * step * \frac{X_j - X_i}{\|X_j - X_i\|} \tag{3}$$

where $rand$ ( ) is a random number generated between 0-1, $step$ is the distance through which a fish moves in one movement, X_i is a position within the scope of the vision of the fish. The position X_j is defined by different behaviours of fish as follows [10,11].

1. Chasing the trail behaviour: The artificial fish will follow the neighbouring fish, which is positioned at a place with more food consistency within its vision scope to find more food. Here X_j is the position of the neighbour.
2. Swarming / gathering behaviour: The artificial fish has a tendency to move to the centre of the swarm in order to ensure the presence of swarm around it and to avoid any potential danger. Here X_j is given by
$$X_j = X_i + rand\,(\,) * step * \frac{X_c - X_i}{\|X_c - X_i\|} \tag{4}$$
where X_c is the centre of the swarm.
3. Foraging / Preying behaviour: The artificial fish senses the food consistence at other locations by vision or sense and determines its movement. When it finds a location with more food around, it directly goes in that direction. The position X_j in this behaviour is given by
$$X_j = X_i + visual * rand\,(\,) \tag{5}$$

2.2 Terms used in the algorithm:

Artificial fish: These are decision variables used in the optimisation problem. The power generated from each generator of this problem form the artificial fishes.
Swarm length: The total number of fishes in the initial swarm.
Step: It is the maximum distance that a fish can move in one movement. In this problem it is the step increment of power generated, i.e., the ramp.
Vision: It is the distance through which the artificial fish can see. In this problem, it is the maximum limit of generation of each generator.

2.3 AFS Algorithm:

Step 1: Generation of initial fish swarm randomly.
Step 2: Initialization of parameters.
Step 3: Evaluation of fitness of each fish in the swarm.
Step 4: Perform chasing the trail behaviour, swarming behaviour and foraging Behaviour on each AF and evaluate new positions. Evaluate the fitness function at each position.
Step 5: Update the best fitness value.

Step 6: Check the termination condition. If not satisfied, go to Step 4

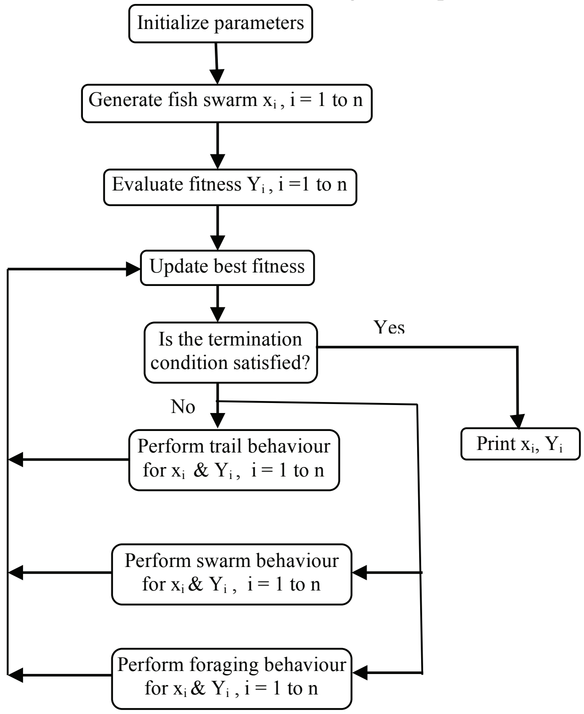

Figure 1. Flow chart of Artificial Fish Swarm algorithm

Figure 1 shows the flow chart to implement AFS algorithm. The three behaviours trailing, swarming and foraging behaviours are performed one after the other if the termination condition is not satisfied.

3. Simulation setup

The cost of generation is considered as utility function for optimization in this article. As introduced in section 2, the cost function can be stated by

$$f\left(p_i(t)\right) = \alpha_i[\,p_i(t)]^2 + \beta_i p_i(t) + \gamma_i\ . \tag{6}$$

The optimization problem can be stated as

$$\begin{aligned} & min \textstyle\sum_{i=1}^{n} f\left(p_i(t)\right) \\ & s.t. \quad \textstyle\sum_{i=1}^{n} p_i(t) = d_i(t) \\ & 0 \leq p_i(t) \leq p_i(t)_{max} \end{aligned} \tag{7}$$

4. Results and discussions

For testing the performance of AFS algorithm, a microgrid in isolated mode investigated in [4] is considered with three wind mills with 750 kW capacity each, two PV plants with a capacity of 200 kW each and one CHP plant of 500 kW capacity over a time duration of 24 hours. The load and the generation are sampled at a time interval of 1 hour. The data for every hour and is given in Table 1 for reference, in which *Pm* denotes the max real power availability. The parameters of cost function α_i , β_i *and* γ_i are chosen from [4] and are as tabulated in Table 2 . The artificial fish algorithm is implemented and the optimal scheduling of generation among the considered RESs is carried out. For validation sake, Additive Increase Multiplicative Decrease algorithm [4] is also implemented by using suitable values for additive parameter *A* and multiplicative parameter *B*. The performance of the AFS algorithm is tested under the following two cases, depending on the access to the CHP source, which is the costliest among the considered sources.

Case-1: In this case, the CHP source is accessed simultaneously along with the remaining sources. Though this case sounds less logical with respect to the economy of generation, still the case is considered to prove the effectiveness of the AFS algorithm in such cases.

Case-2: In this case, the CHP source is accessed only when all the remaining cheaper sources are exhausted. This is a realistic optimization case and mimics a either grid connected microgrid or interconnected microgrids, where the CHP source can be replaced by grid or other microgrid.

Table 1. Maximum power availability of each source

Hour	Pmaxw1	Pmaxw2	Pmaxw3	Pmaxpv1	Pmaxpv2	demand
0	660	688	429	0	0	1471
1	699	707	442	0	0	1325
2	740	698	220	0	0	1263
3	723	699	39	0	0	1229
4	666	576	21	0	0	1229
5	558	675	167	0	0	1321
6	669	674	351	0	15	1509
7	666	693	532	10	71	1663
8	719	732	497	67	90	1657
9	711	746	504	98	116	1643
10	711	686	507	122	140	1643
11	716	661	366	139	155	1652
12	706	638	372	145	163	1666
13	678	561	195	145	163	1639
14	697	650	74	133	155	1642
15	709	652	23	120	133	1640
16	693	657	138	94	107	1676
17	707	660	381	61	86	1920
18	721	659	617	17	46	2214
19	644	668	652	0	1	2382
20	674	664	706	0	0	2382
21	677	661	744	0	0	2327
22	688	642	696	0	0	2174
23	694	674	711	0	0	1903
24	672	649	72	0	0	1666

Table2 . Cost function parameters of RESs

Plant	a_i	b_i	c_i
Wind plant 1	0.0027	17.83	4.46
Wind plant 2	0.0028	17.54	4.45
Wind plant 3	0.0026	17.23	4.44
Solar PV 1	0.0055	29.30	4.45
Solar PV 2	0.0055	29.58	4.46
CHP	0.0083	75.73	5.21

The possibility of using storage devices to enhance the reliability of the microgrid are not considered in either case, as the aim of this article is only to endorse the applicability of the AFS algorithm for economic generation scheduling in a microgrid.

Table 1 shows the hourly maximum power availability of each renewable source. The scheduled generation using AFS algorithm is as tabulated in Table 3 for case-1 and in Table 4 for case-2. Figures 2(a) and 3(a) summarise the generation scheduling simulated by AFS algorithm for both the cases. Table 3 and Table 4 confirm that the total generation scheduled by the AFS algorithm exactly matches the demand which endorses the applicability of the algorithm for economic generation scheduling in a microgrid. The costs of generation as estimated by AIMD algorithm and AFS algorithm are tabulated in the cost columns of Table 3 and Table 4.It shows that the AFS algorithm is a class ahead in economic scheduling compared to AIMD algorithm. In both the cases, from the 0^{th} hour to 18^{th} hour, where the surplus power availability is more, the ability of AFS algorithm is much more pronounced because there is a larger choice of generators to choose from. More surplus power availability enables larger search space and more no of artificial fish locations are generated and hence the algorithm is able to find a better economic mix of generation, which the AIMD algorithm is unable to do. On the other hand, AIMD algorithm simply schedules generation among the available generators equally at the end of given number of iterations by adding a fixed increment *A* for each iteration, subject to the maximum power availability with the respective generator, which can be seen from the Table3 and Table4. The CHP source being the costliest source, even a small reduction in its generation allocation brings a large difference in the generation cost and this is the reason for large difference between the costs evaluated by the two algorithms in case-1. During 19th to 23rd hours, the saving in cost as calculated by AFS algorithm is less for the reason that the surplus power availability is much less, which results in a

Table 3. Results of generation scheduling using AIMD and AFS algorithms for case-2

Hour	Scheduling using AIMD algorithm (kW)						Scheduling using AFS algorithm (kW)						Cost (USD)	
	Pwind1	Pwind2	Pwind3	AIMD	AIMD	Pchp	Pwind1	Pwind2	Pwind3	Ppv1	Ppv2	Pchp	AIMD	AFS
0	521	521	429	0	0	0	521	521	429	0	0	0	53.29	53.26
1	441.65	441.65	441.65	0	0	0	217	685	423	0	0	0	50.69	50.64
2	521.58	521.58	219.82	0	0	0	377	671	215	0	0	0	49.7	49.67
3	595	595	39	0	0	0	595	595	39	0	0	0	49.19	49.17
4	632	576	21	0	0	0	632	576	21	0	0	0	49.21	49.21
5	558	596	167	0	0	0	558	596	167	0	0	0	50.75	50.73
6	571.6	571.6	350.75	0	14.99	0	562	618	328	0	1	0	54.17	54
7	527.37	527.37	527.37	9.99	70.91	0	606	526	521	8	2	0	57.48	56.77
8	501.7	501.7	496.7	66.96	89.95	0	482	667	492	1	15	0	58.39	56.71
9	476.41	476.41	476.41	97.88	115.86	0	511	654	470	5	3	0	58.1	56.38
10	460.43	460.43	460.43	121.8	139.83	0	702	478	451	2	10	0	58.17	56.49
11	496	496	366	139	155	0	496	496	366	139	155	0	59.98	56.77
12	493	493	372	145	163	0	493	493	372	145	163	0	60.39	57.53
13	575	561	195	145	163	0	575	561	195	145	163	0	59.99	59.26
14	640.17	640.17	73.9	132.8	154.8	0	640	641	74	132	155	0	59.86	59.86
15	709	652	23	120	133	3	709	652	23	120	133	3	59.62	59.62
16	680.56	656.57	137.91	93.94	106.93	0	681	656	138	94	107	0	59.41	59.41
17	707	660	381	61	86	25	707	660	381	61	86	25	64.44	64.44
18	721	659	617	17	46	154	721	659	617	17	46	154	76.04	76.04
19	644	668	652	0	1	417	644	668	652	0	1	417	93.52	93.52
20	674	664	706	0	0	338	674	664	706	0	0	338	88.9	88.9
21	677	661	744	0	0	245	677	661	744	0	0	245	82.51	82.51
22	688	642	696	0	0	148	688	642	696	0	0	148	74.2	74.2
23	634.33	634.33	634.33	0	0	0	671	566	666	0	0	0	60.84	60.84
24	672	649	72	0	0	273	672	649	72	0	0	273	72.75	72.75
								Total cost of generation over 24 hours					1561.59	1548.68

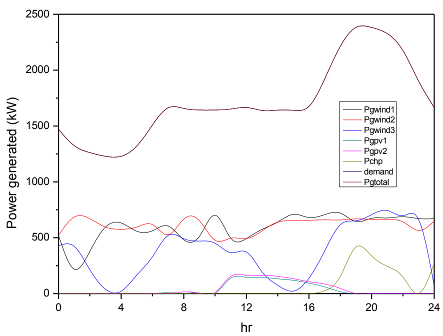

Figure 2 (a)

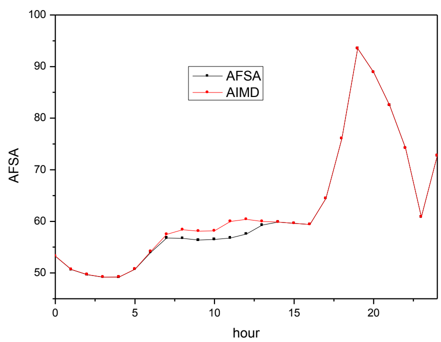

Figure 2 (b)

Figure 2 (a) Scheduled generation vs time as calculated by AFS algorithm in case -1
(b) Cost comparison as estimated by AIMD and AFS algorithms

lesser search space for the Artificial Fish. At end of the day, the AIMD algorithm puts the total cost of generation over 24 hours at USD 2075.39 in case-1 and at USD 1561.56 for case-2, where as AFS algorithm puts the same at USD 1685.26 for case-1 and USD 1548.68 for case-2, with a net saving of USD 390.13 and 12.91 respectively in each case. Figures 2(b) and 3(b) summarise the trends of hourly cost of generation as calculated by AFS algorithm and AIMD algorithm for the two cases. The cost difference is much more glaring in Case 1, because as already demonstrated, the AFS algorithm explores the search space for best location of artificial fish, which gives the best fitness value i.e., optimal cost of generation.

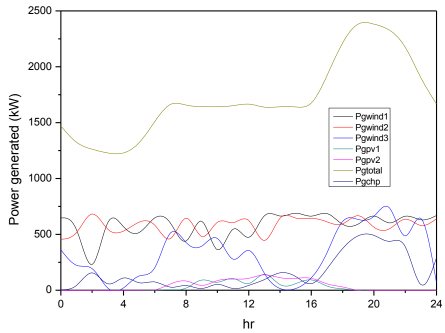

Figure 3 (a)

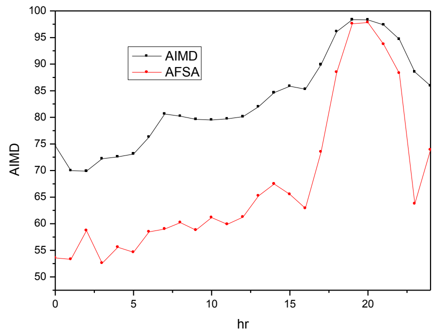

Figure 3 (b)

Figure 3 (a) Scheduled generation vs time as calculated by AFS algorithm in case -2
(b) Cost comparison as estimated by AIMD and AFS algorithms

5. Conclusions

The fast depleting conventional energy sources are urging the energy sector to shift its dependency to the RESs. Moreover the advances in DG and RES technologies are so attractive that the energy sector cannot overlook them. But the uncertainty in the power availability of the RESs is posing operational problems to maintain balance and stability. In spite of these odds, the liberalised energy policies by the governments are very promising to the private power producers and there is a strict competition in the energy markets. A variety of optimization algorithms are in use and are being developed by research to address the problem of optimized utilization of DG and RESs based on day ahead forecasted statistics. In this paper AFS algorithm is used to schedule generation economically in a microgrid with uncertain sources under two cases. In case 1, the improvement in cost reduction by the AFS algorithm is much glaring, as the costliest source is accessed simultaneously along with the other sources. Also in case 2, which is a more realistic one, in which the costliest source is accessed only after all the cheaper sources are exhausted, the AFS algorithm is performing reasonably good. A comparison is made between AFS algorithm and AIMD algorithm for validation, by using them to schedule generation in a microgrid comprising of three wind, two solar PV and a CHP generators isolated mode with a load curve of a few MW over 24 hour time schedule at a time interval of 1 hour. The AFS algorithm is proved to be much more competitive in economic scheduling of generation compared to AIMD algorithm.

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