IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676, p-ISSN: 2320-3331, Volume 16, Issue 6 Ser. I (Nov. – Dec. 2021), PP 38-47
www.iosrjournals.org

Energy Resource Allocation for a Rural Microgrid: Comparison Using Linear and Nonlinear Optimization Approaches

[1]Yuvraj Praveen Soni, [1]Eugene Fernandez, [2]M. Mustafa Kamal, [2]Imtiaz Ashraf
[1]Indian Institute of Technology Roorkee, India, [2]Aligarh Muslim University, India

Abstract. *Most of the reported work in the literature on energy resource allocation planning for rural areas uses optimisation algorithms, of which the most widely used is the Linear Programming (LP) approach. However, it is felt that improved results can be obtained when the linear form used in LP is solved using nonlinear algorithms. This paper has attempted to investigate three nonlinear algorithms to solve the energy allocation problem for a rural microgrid concerning the LP algorithm solution. The proposed nonlinear algorithms are the Simulated Annealing algorithm (SA), the popularly used Genetic Algorithm (GA) and a new approach that is being currently promoted in the literature as the Differential Evolution (DE) algorithm. Taking the case of reported data of a hilly rural village from Uttarakhand State in Northern India, the nonlinear algorithms are compared with the results obtained using linear programming. The result obtained in this analysis propound DE algorithms followed by GA and SA for best results. In general, it is seen that these nonlinear algorithms can give better-optimised results compared with LP.*

Index Terms— *Comparative evaluation, Linear Programming, Nonlinear programming algorithms, Optimisation methods, Rural energy allocation*

Date of Submission: 10-12-2021 Date of Acceptance: 24-12-2021

I. INTRODUCTION

Remote communities electrification with renewable energy integration has attracted performance analysis planners [1] – [5] with the utilisation and development of numerous statistical tools. These studies suggest that renewable energy systems can be used profitably for designing dependable energy providing systems. Two significant types of energy studies are popular, namely sizing and control of integrated rural energy systems for specified load demand [6] – [10].

The energy planning studies generally involve the use of optimisation structured objectives. Linear programming (LP) has been a much-used tool for planning in several studies. Of late, a few studies [11] – [15] explore the use of nonlinear programming algorithms [16] – [19] However, there are virtually no studies that contrast the performance of such algorithms with LP. This paper is an attempt in this direction.

In this paper we investigate with respect to the LP algorithm, three non linear algorithms to solve the energy allocation problem for a rural microgrid. While there are several varieties of nonlinear programming algorithms, we limit the analysis to only three kinds, namely, the Simulated Annealing algorithm (SA), the popularly used Genetic Algorithm (GA) and a new approach that is being currently introduced in the literature as the Differential Evolution (DE) algorithm. Taking the case of reported data of a rural hilly village from Uttarakhand State in Northern India, the three algorithms are tested for comparison of best optimised outputs.

II. DATA OF THE STUDY AREA

Data for the investigation is referred from reference [20]. This data pertains to a rural hilly area located in Uttarakhand state in India. Table I shows the general data related to the study area.
Figure 1 shows the projected average hourly load profiles for two seasons of the study area, i.e., summer and winter seasons.

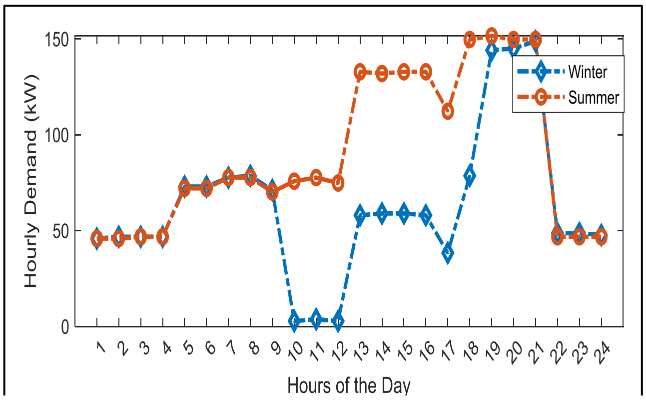

Fig 1. Hourly load profile of two seasons

Table I
Basic information of study area

S. No.	Item	Total
1.	Country	India
2.	State	Uttarakhand
3.	District	Tehri Garhwal
4.	Boundary districts	Rudraprayag district - East Dehradun - West, Uttarkashi - North Pauri Garhwal - South.
5.	Population (as per 2011 census)	618,913
6.	Total Area of district	36242 square kilometers
7.	Name of block (study area)	Jaunpur
8.	No. of Villages in study area	259-total 202- electrified 57- un-electrified 24- electrified by renewable energy by Uttaranchal Renewable Development Agency (UREDA)
9.	Total number of *panchayats* (local administrative units)	111
10.	Number of available water springs	33
11.	Number of available waterfalls	09
12.	Number of reserve forests	23
13.	Number of installed water mills (*Gharat's*)	53

Source: Akella, Sharma and Saini, (2007) [20]

Table II.
Potential of Available energy resources in the area

S. no.	Available type of generation	Maximum capacity (kWh/m^2/yr.)
1.	Micro-hydro power	128166.00
2.	Solar photovoltaic power	22363.00
3.	Wind energy	15251.00
4.	Biomass energy	641385.00

Source: Akella, Sharma and Saini, (2007) [20]

Table III.
Efficiency of the various energy conversion systems

S.no.	Energy conversion system	Efficiency
1.	Micro hydro power (MHP)	0.90
2.	Solar photovoltaic power (SHP)	0.90
3.	Wind Energy System (WES)	0.80
4.	Biomass Energy System (BES)	0.85

Source: Akella, Sharma and Saini, (2007) [20]

Table IV.
Total energy demand for different activities

S.no	Type of energy activity	Average Energy demand (MWh/year)
1	Domestic	664
2	Motive power/Local industries	23
3	Agriculture	0.114
4	Local transport	0
	Total (approx.)	687

Source: Akella, Sharma and Saini, (2007) [20]

Table V.
Effective considered cost of operation for various generation options

S.No.	Energy conversion system	Cost (Rs/kWh)
1.	Micro hydro power (MHP)	1.50
2	Solar photovoltaic power (SHP)	15.27
3	Wind Energy System (WES)	3.50
4	Biomass Energy System (BES)	3.10

Source: Akella, Sharma and Saini, (2007) [20]

Table VI.
Results of Optimisation using LP

S. NO.	EPDF	Objective Function / Optimal Cost (Rs)	MHP (kWh)	SPV (kWh)	WES (kWh)	BES (kWh)
1	1.00	2134710	115465	15588	12201	543546
2	0.75	4176533	86599	183391	9151	407660
3	0.5	1613229	398853	10073	6100	271773
4	0.35	1438320	485237	7051	4270	190241
5	0.25	1321715	542826	5037	3050	135886

Source: Akella, Sharma and Saini, (2007) [20]

III. THE LINEAR MODEL

Formulation of objective function "Z" [20] for cost minimisation is developed using the data available in Table II-V to arrive at the output, which will lead to system operation at least cost. Objective function Z is as shown:

$$\text{Minimize } Z = 1{:}50\ MHP + 15{:}27\ SPV + 3{:}50\ WES + 3{:}10\ BES \quad \textbf{(1)}$$

$$\text{which is Subject to : } MHP + SPV + WES + BES = D \quad \textbf{(2)}$$

$$\frac{MHP}{0.90} \leq 128{,}166\ \frac{kWh}{m^2.yr} \quad \textbf{(3)}$$

$$\frac{SPV}{0.90} \leq 22{,}363\ \frac{kWh}{m^2.yr} \quad \textbf{(4)}$$

$$\frac{WES}{0.80} \leq 15{,}251\ \frac{kWh}{m^2.yr} \quad \textbf{(5)}$$

$$\frac{BES}{0.90} \leq 641{,}385\ \frac{kWh}{m^2.yr} \quad \textbf{(6)}$$

$$WES, SPV, BES, \text{ and } MHP \geq 0 \quad \textbf{(7)}$$

where, $D = 686{,}800\ \frac{kWh}{yr}\ or\ 687\ \frac{MWh}{yr}$

MHP=Micreo-hydropower plant power supply
SPV=Solar power plant power supply,
BES=Biogas gasifier electricity generation,
WES=Wind Energy System Power supply

Considering the intermittent nature of renewable energy leading to non-regular availability literature, [20] introduced a factor called Effective Power Delivery Factor (EDPF) to estimate the reduced power available concerning the designed output capacity. EPDF is described as the power extracted per season to the maximum power extracted per season 'theoretically' as represented in equation (8).

$$EPDF = \frac{\text{power obtained per season}}{\text{maximum power possible per season}} \quad \textbf{(8)}$$

Making use of EPDF factor creates different sub-models, which an optimisation algorithm may investigate. The solution of the model given above using LP shows the following results (Table VI).

There may be a possibility of obtaining improved optimisation results with the linear form used in the case of LP by using nonlinear algorithms. To test this hypothesis, we optimise the objective function for LP using nonlinear optimisation algorithms.

In the literature a variety of nonlinear algorithms are available. These include a vast category of meta-heuristic approaches [16] – [19] As the main objective of this paper is to explore the effectiveness of alternative forms i.e., nonlinear algorithms vis'-a-vis the LP approach, the work was narrowed down to a comparative study using certain selected nonlinear optimisation algorithms with the results obtained using LP. To test the hypothesis that nonlinear algorithms can yield better results than LP, we have analysed the outputs of three meta-heuristic nonlinear algorithms. It is felt that three nonlinear algorithms may provide general trends. However, more nonlinear optimisation algorithms may be tried to obtain more conclusive evidence.

The three nonlinear algorithms selected for investigations are the SA, GA, and a new approach called the Differential Evolution (DE) algorithm. Thus, this paper implements a linearised form of an objective function to the mentioned optimisation algorithm in MATLAB. The algorithms are as follows –

1)Simulated Annealing Algorithm (SA)
2)Genetic Algorithm (GA)
3)Differential Evolution (DE)

The following section presents a brief overview of these optimisation algorithms.

IV. NONLINEAR OPTIMISATION USING SA, GA AND DE

A. Simulated Annealing (SA)

The Simulated Annealing algorithm has been explained in the literature as a nonlinear optimisation tool [21] – [24]. In 1963, SA method was proposed by Kirkpatrick, Gelatt, and Vecchi. SA utilises the nature of cooling of heated metal with a path-based arbitrary search algorithm to reach the global optimised value. SA transforms the objective function into a metal annealing process. With the advantage of its applicability to numerous problems that may involve a highly nonlinear system with noisy data and several other constraints [22], the method is considered a robust and flexible technique. Initially, SA was applied for a nonlinear problem solution which involves several exponential steps to find an exact answer. The key advantages of the SA technique vis-a vis' the conventional local search-based heuristic methods are that the SA can avoid being trapped in a locally optimal solution during its execution [23]. The major disadvantage with SA is the long computational time. Various reports in the literature use SA in cost optimisation problems [21], [24].

Generally, optimisation algorithms work upon comparing its current iterative outputs of the objective function by its neighbouring points in the domain. Every next iteration considers its neighbour point and is validated to give a better solution than the present point. If the current iteration provides a better result, then the solution is updated to the current point; otherwise, the previous point is retained as the best value. This optimising algorithms generally involves searching results into a limited domain, making the algorithm prone to local minima or maxima trapping. Unlike the general optimisation technique, the SA algorithm uses an annealing process loop and a second loop for the metropolis process to reach the optimum global value.

Let us consider an objective function $f(x_i)$ for minimisation problem for argument set of $x_i = x_1, x_2, \cdots, x_n$ with $n \in \Re$. The solution will be searched through the defined algorithm, and if $f(x_{i+1} < f(x_i))$, then x_{i+1} will be considered for the next iteration. Else, $\omega = e^{\frac{-(f(x_{i+1})+f(x)_i)}{T_C}}$ is determined where T_c is the current temperature parameter and generates a random number s, such that 0 < s < 1. Further if $\omega > s$ is true then x_{i+1} will also be accepted as new candidate; else if the case does not match the criterion, X_{i+1} will be rejected, and another s will be generated through the previous step. Even though the path of the objective function is getting convergent, the metropolis criterion allows for the motion of the current stage to a certain extent through the potential minimum points.

At the beginning of the SA algorithm, an enormous temperature value is considered, implemented in the inner loop to determine the best candidate solution from objective function computation. Whereas in the outer loop, the temperature is incremented and updated until it reaches the minimum temperature or maximum iteration count.

SA algorithm considers an immense value of temperature at the beginning stage to execute the inner loop iteration. The value resulting in the best objective function in the inner loop is immediately taken as a new candidate solution. For the output loop, the temperature is incremented and updated at starting point. This process continues until it reaches the lowest temperature limit or if the iteration count limit is reached.

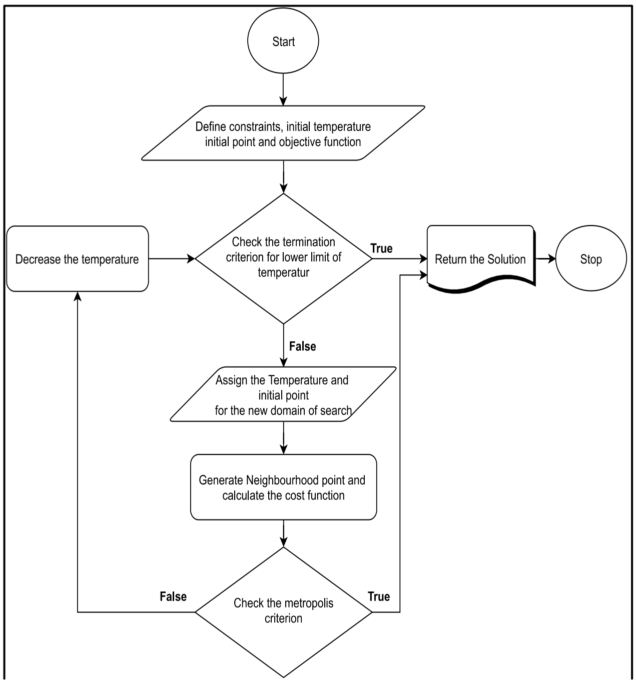

Fig. 2. Basic Algorithm of Simulated Annealing

B. Genetic Algorithm (GA)

GA is a dedicated search algorithm that imitates the growth of the genetic species. Holland proposed GA as a simplified and effective optimisation algorithm. The advantage of the GA is that the objective function can be treated as a black box problem to optimise the given situation. GA begins with the preliminary arbitrarily search and gradually improves the solution of the defined problem in successive steps. The method may converge speedily to reach a global optimum. The critical advantage of GA is that it performs a similar global search, which diminishes the risks related to stagnation at local optima. The disadvantage of the Genetic Algorithm procedure is that the programmer is not exactly clear whether the best global optimum has been attained. Literature is available on the use of GA to optimise renewable energy problems [25] – [29].

Figure 3 shows the basic flow chart for the GA. An initial population of possible solutions is randomly generated and subject to test suitability with a fitness function screens the unlikely solution choices. The remainder is then magnified as a new population and tested. Processes like crossover and mutation are also introduced to ensure that the optimal solutions obtained are not trapped in local optima. Finally, the best solution values are selected based on the convergence limits set. The essential steps of the algorithm are explained as follows:

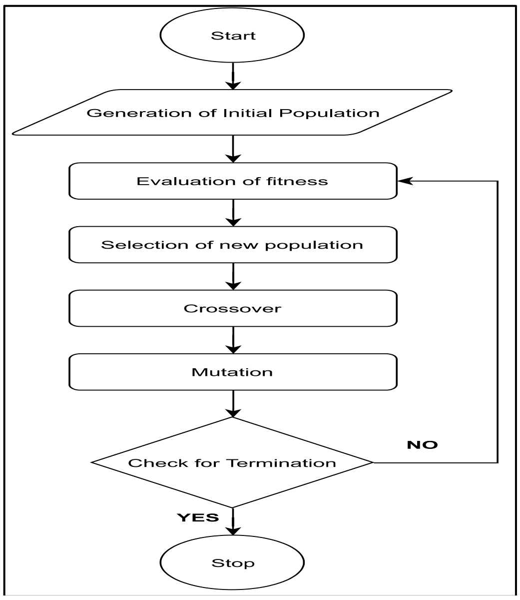

Fig. 3 Flow Chart of Genetic Algorithm

Step 1: Generate the initial population strings of possible solutions.
Step 2: Evolve a fitness function and test the initial population of possible solutions.
Step 3: Filter out the favourable possible solutions.
Step 4: Magnify the possible feasible solutions as a new population to be further tested.
Step 5: Subject the new population to processes like mutation and cross over to avoid the local minima trap.
Step 6: Test the proposed solution again with the fitness function.
Step 7: If an acceptable solution is obtained based on the convergence limits set, print solution and end.
Step 8: If not, redo steps 3-7.
Step 9: Select the best solution based on the convergence limits set.

C. Differential Evolution (DE)

Differential evolution (DE) is a meta-heuristics method that converges to the potential solution regarding a set measure of quality through iterative optimisation. Storn and Price originally conceived DE. Such practices make few assumptions about the problem being optimised and can search vast spaces of candidate solutions. However, they do not necessarily guarantee an optimal solution. DE has been discussed in several reports and studies [30] – [35].

Unlike Gradient Descent and Quasi-Newton methods, DE does not utilise the gradient of the problem, implying that DE does not impose on the problem to be differential. It gives DE an advantage over other optimisation techniques and can be applied to a noisy, discontinuous problem or a problem that changes over time. The Basic DE algorithm is illustrated in Figure 4.

DE algorithm optimises a problem by considering the population of the candidate solution and creating a new population by regrouping according to simple formulae. It retains the candidate which provides the best solution. The algorithm is considered a black box that offers a measure of quality given a candidate solution, and therefore the gradient is not needed. The DE algorithm is described as follows: [35]

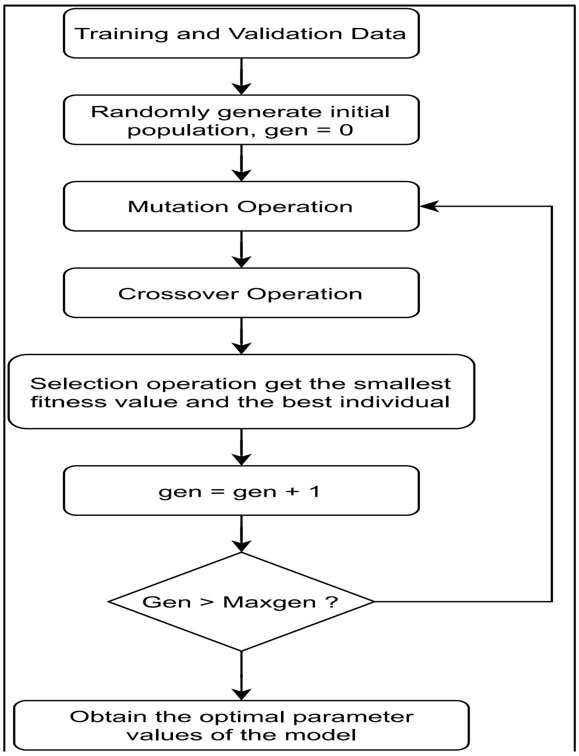

Fig. 4 Basic DE Algorithm

Step 1: Initialisation

N_p vectors within the boundary of $X_{ij}^{0} \sim Rand(X_j^{\min}, X_j^{\max})$ is generated randomly for all the variables to generate set of initial population. Where, $i = 1,\cdots,N_p$ and $j = 1,\cdots,D$. $X_j^{\min}$ and $X_j^{\max}$ are the lower and upper bound of the j^{th} decision variable. $Rand(X_j^{\min}, X_j^{\max})$ represents a uniform random variable ranging over $[X_j^{\min}, X_j^{\max}]$. X_{ij}^{0} represents initial variable which is randomly generated at j in i^{th} population and all of the initial population values must satisfy the defined constraints.

Step 2: Fitness function-based evaluation
Fitness function $f(X_i^0)$ or objective function values for all generated vectors are calculated.

Table VII.
Total cost of energy by different algorithms in INR (Indian Rupees)

S. No	EPDF	Linear Programming (LP) (Akella, Sharma and Saini, 2007)	Simulated Annealing (SA)	Genetic Algorithm (GA)	Differential Evolution (DE)
1	1.00	2134710	2166213	2121733	2120700
2	0.75	4176533	1992230	1601264	1590500
3	0.50	1613229	1726643	1061798	1060300
4	0.35	1438320	974043	743045	742230
5	0.25	1321715	628658	530881	530170

Step 3: Mutation
DE generates a new parameter or target vector by random selection of three different members from the population. The mutant vector X_i^{mg} is obtained by

$$X_i^{mg} = X_a^g + F(X_b^g - X_c^g),\ i \sim N_p \qquad \textbf{(9)}$$

Where $X_a^g, X_b^g, and\ X_c^g$ defines members selected randomly from population vectors at g^{th} generation and $a \neq b \neq c \neq i$. Scaling Factor (F) in the range of $0 < F < 1.2$ controls the perturbation value that can be added to the parent vector to form a mutant vector. Also, the mutant vector generated should be within the defined constraints.

Step 4: Crossover
Crossover is a process where the initial vector and mutant vector X_i^{mg} are swapped together to form another vector called "trial vector" **-** X_i^{tg}. The trial vector X_i^{tg} can be defined as –

$$X_i^{tg} = \begin{cases} X_i^{tg} & if\ p < C_R \\ X_i^{mg}, & otherwise \end{cases} \qquad \textbf{(10)}$$

Where C_R = crossover constant and ranges from 0-1, which controls population diversity and supplements the algorithm to converge in the global optimum solution instead of getting settled with local optima. ρ is a uniformly distributed random number between [0-1].

Step 5: Selection
The fitness values of the initial vectors (X_i^0) and the trial vector (X_i^{tg}) are compared for selecting each parameter of the target vector. The vector that has lesser fitness of the two would survive for the next generation.

$$X_i^{tg} = \begin{cases} X_i^{tg} & if\ X_i^{tg} \leq f(X_t^g) \\ X_i^g, & otherwise \end{cases} \qquad \textbf{(11)}$$

The process will repeat until it reaches the maximum iteration number or there is no significant improvement in the fitness values for many iterations.

V. RESULTS AND DISCUSSION

As discussed earlier, the objective of the present work is to examine if nonlinear optimisation algorithms can yield a better optimal solution than LP for the linear objective function. This has been reviewed here with respect to three nonlinear metaheuristic algorithms, namely, SA, GA, and DE. Reduced inputs have also been considered (EPDF), which consider the non-continuous availability of renewable energy input resources. The EPDF varies from 1.0 to 0.25. For the value of EPDF 1.0 indicated, the plant delivers maximum energy to the load.

Similarly, 0.75 indicates a 25% reduction in the energy delivery capability of the plant. The present model also considers the possible loss or non-functioning of any one of the energy resources, which will then affect overall energy delivery. Table VII gives the results of the simulations using the different algorithms.

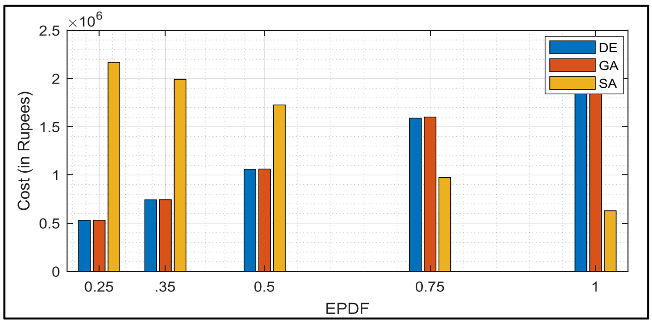

Fig. 5 Relative Cost of Energy at Different EPD

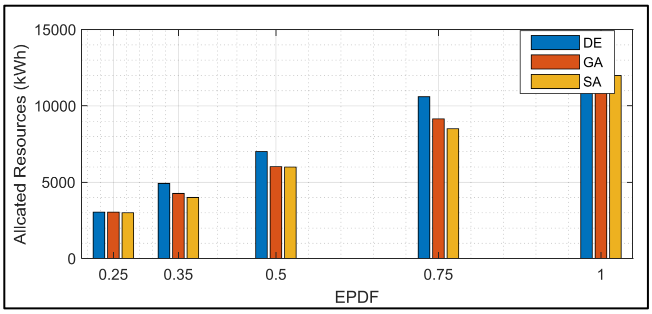

Fig. 6 Resource Allocation of SPV for different EPDF value

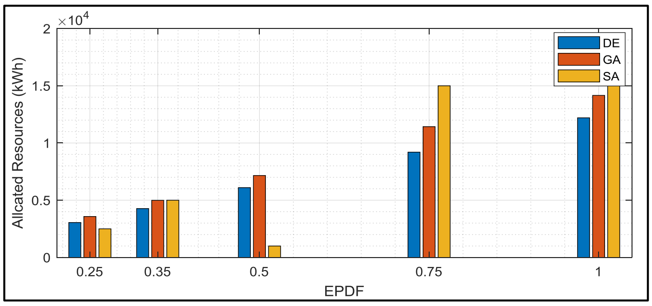

Fig. 7 Resource allocation of WES for different EPDF

Diversity is observed in the final solution for each algorithm when implemented for the resource allocation problem. Every algorithm provides a different solution for energy supply through different distributed energy resources. It may be seen from Table VII that LP shows the maximum cost of the three algorithms for most cases of EPDF. With SA, specific values of EPDF show worse results as compared with LP. However, GA and DE both show consistent lesser values than the corresponding values for LP for a given EPDF. Of the two (i.e., GA and DE), DE shows better results. Thus, nonlinear algorithms, when used with linear objective functions, can yield better solutions than LP. Further, of the considered nonlinear algorithms, DE appears to provide better results than GA and SA.

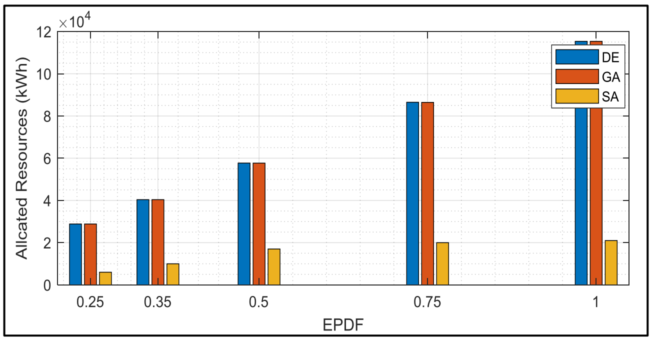

Fig. 8 Resource allocation of MHP for different EPDF

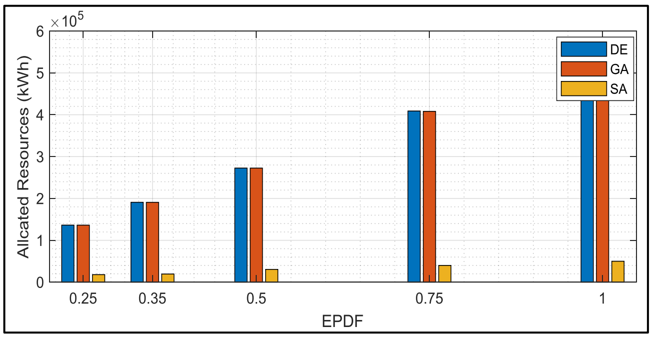

Fig. 9 Resource allocation of BES for different EPDF

Figures 5-9 show the overall cost and allocations of the energy resources for the optimised values given in 7 in an understandable form to highlight the relative differences in the optimised values for different optimisation algorithms.

Figures 5-9 represents the variation of resource allocation of different sources with different algorithm applied. We follow each method for various resources; source allocation does not follow a fixed pattern. The outcome depends upon the process algorithm follows to arrive at its potential solution.

However, the rural planner will emphasise total cost expense for energy generation and operation rather than on energy allocation for different resources with the same operating constraints. With this evidence, a conclusion can be drawn that as compared to the SA technique, DE is a more effective algorithm for implementation. However, further exploration of the DE optimisation technique may be required as this paper considers a single case. Further, if it provides a better result, it can be set as a trend for distribution system optimisation. Also, other nonlinear algorithms like PSO, Ant colony optimisation etc., maybe try to see if the trends observed here can be safely generalised.

VI. CONCLUSION

This paper presents the relative effectiveness of different optimisation techniques applied for the rural sector's energy resource planning. Using the data available for Indian rural villages, planning for the least cost is evaluated with LP, SA, GA, and DE optimisation techniques. Results show that DE is the best among LP, SA and GA algorithms while LP is the least effective. Through different sub-models effectiveness of the algorithm are tested with the intermittent nature of renewable energy sources. In each case, it is found that DE provides the best results. In general, it is observed here that nonlinear algorithms used for linearised objective functions produce better optimised objective function values than LP. However, further investigations with other nonlinear optimisation algorithms are called for utilisation and application for the energy resource allocation problem to generalise this statement.

REFERENCES

[1]. Chauhan, A. and Saini, R. P. (2016). Techno-economic optimisation-based approach for energy management of a stand-alone integrated renewable energy system for remote areas of India. Energy. 94, 138-156. DOI: https://doi.org/10.1016/j.energy.2015.10.136.

[2]. Rajanna, S. and Saini, R. P. (2016). Modeling of integrated renewable energy system for electri_cation of a remote area in India. Renewable Energy. 90, 175-187. DOI: https://doi.org/10.1016/j.renene.2015.12.067

[3]. Ramakumar, R., Shetty, P. S. (1983). Renewable Energy Sources and Developing Countries. IEEE Transactions on Power Apparatus and Systems. 102 (2), 502-510. DOI:10.1109/TPAS.1983.317720

[4]. Sanajaoba, S. and Fernandez, E. (2016). Maiden application of Cuckoo Search algorithm for optimal sizing of a remote hybrid renewable energy System. Renewable Energy. 96 (Part A), 1-10. DOI: https://doi.org/10.1016/j.renene.2016.04.069

[5]. Singh, S., Singh, I. P., Singh, S., Pannu, CJS. (1996). Energy planning of a Punjab village using multiple objectives compromise programming. Energy Conversion and Management. 37 (3), 329-342. DOI: 10.1016/0196-8904(95)00180-8

[6]. Bagul, A. D., Salameh, Z. M., Borowy, B. (1996). Sizing of stand-alone hybrid wind photovoltaic system using a three-event probability density approximation. Solar Energy. 56 (4), 323-335. DOI: https://doi.org/10.1016/0038-092X(95)00116-9

[7]. Chedid, R, Saliba, Y. (1996). Optimisation and control of autonomous renewable energy systems. International Journal of Energy Research. 20 (7), 609-624. DOI: https://doi.org/10.1002/(SICI)1099114X(199607)20:7<609::AIDER176>3.0.CO;2-O

[8]. Habib, M. A., Said, S, El-Hadidy, M. A., Al-Zaharna, I. (2009). Optimisation procedure of a hybrid photovoltaic wind energy system. Enegy. 24 (11), 919-929. DOI: https://doi.org/10.1016/S0360-5442(99)00042-0

[9]. Kellogg, W. D., Nehrir, M. H., Venkataramanan, G., Gerez, V. (1998). Generation unit sizing and cost analysis for stand-alone wind photovoltaic and hybrid wind/PV systems. IEEE Trans Energy Convers. 13 (1), 70-75. DOI: 10.1109/60.658206

[10]. Nfaoui, H., Buret, J., Sayigh, A. M. M., Dunn, P. D. (1994). Modelling of a wind/diesel system with battery storage for Tangier Morocco. Renewable Energy. 4 (2), 155-167. DOI: 10.1016/0960-1481(94)90001-9

[11]. Joshi, B., Bhatti, T. S., Bansal, N. K. (1992). Decentralised energy planning model for a typical village in India. energy. 17 (9), 869-876. DOI: https://doi.org/10.1016/0360-5442(92)90104-8

[12]. Ramakumar, R., Shetty, P. S., Ashenayi, K. (1986). A Linear Programming Approach to the Design of Integrated Renewable Energy Systems for Developing Countries. IEEE Transactions on Energy Conversion. 1 (4). DOI: 10.1109/TEC.1986.4765768

[13]. Rijal K., Bansal, N. K., Grover, P. D. (1990). Rural household energy demand modeling. Energy Economics. 12 (4), 279-288. DOI:https://doi.org/10.1016/0140-9883(90)90018-B.

[14]. Subhash, C., Satsangi, P. S. (1990). An integrated planning and implementation-strategy for rural energy systems. Energy. 15 (10), 913-920. DOI: https://doi.org/10.1016/0360-5442(90)90073-B

[15]. Zhen, F. (1993). A model of the energy-supply and demand system at the village level. Energy. 18 (4), 365-369. DOI: https://doi.org/10.1016/0360-5442(93)90071-K

[16]. Arabali, A., Ghofrani, M., Etezadi-Amoli, M., Fadali, M.S., and Baghzouz, Y. (2013). Genetic Algorithm Based Optimisation Approach for Energy Management. IEEE Transactions on Power Delivery. 28 (1), 162-170. DOI: 10.1109/TPWRD.2012.2219598

[17]. Bernal-Agustin, J. L., Dufo-Lopez, R. (2009). Efficient design of hybrid renewable energy using evolutionary algorithms. Energy Conversion and Management. 50 (3), 479-489. DOI: https://doi.org/10.1016/j.enconman.2008.11.007

[18]. Chauhan, A. and Saini, R. P. (2016). Discrete harmony search based size optimisation of Integrated Renewable Energy System for remote rural areas of Uttarakhand state in India. Renewable Energy. 94, 587 - 604. DOI:https://doi.org/10.1016/j.renene.2016.03.079

[19]. Hakimi, S. M., Moghaddas-Tafreshi, S. M. (2009). Optimal sizing of a stand-alone hybrid power system via particle swarm optimisation for Kahnouj area in south-east of Iran. Renewable Energy. 34 (7), 1855-1862. DOI: https://doi.org/10.1016/j.renene.2008.11.022

[20]. Akella, A. K., Sharma, M. P., and Saini, R. P. (2007). Optimum utilisation of renewable energy sources in a remote area. Renewable and Sustainable Energy Reviews. 11 (5), 894-908. DOI: https://doi.org/10.1016/j.rser.2005.06.006

[21]. Ekren O. and Ekren, B. Y. (2010). Size optimisation of a PV / wind hybrid energy conversion system with battery storage using simulated annealing. Applied. Energy, 87 (2), 592-598. DOI: https://doi.org/10.1016/j.apenergy.2009.05.022

[22]. Sinha, S. and Chandel, S. S. (2015). Review of recent trends in optimisation techniques for solar photovoltaic wind-based hybrid energy systems. Renewable and Sustainable Energy Reviews. 50, 755-769. DOI:https://doi.org/10.1016/j.rser.2015.05.040

[23]. Suppapitnarm, A., Se_en, K.A., Parks, G.T., Clarkson. P,J. (2007). A Simulated Annealing Algorithm for Multiobjective Optimisation. Engineering Optimisation. 33 (1), 59-85. DOI: https://doi.org/10.1080/03052150008940911

[24]. Zhang, W., Maleki, A., Rosen, M. A., and Liu, J. (2018). Optimisation with a simulated annealing algorithm of a hybrid system for renewable energy including battery and hydrogen storage. Energy, 163, 191-207.

[25]. Bakhshi, R., Sadeh, J., Mosaddegh, HR. (2014). Optimal economic designing of gridconnected photovoltaic systems with multiple inverters using linear and nonlinear module models based on Genetic Algorithm. Renewable Energy. 72, 386-394. DOI: https://doi.org/10.1016/j.renene.2014.07.035

[26]. Gota, D., Domuta, C., and Miclea L. (2012). Design and Control of Smart Hybrid Renewable Energy Systems Using Modi_ed Genetic Algorithms and Direct Design Control. 2012 Asia-Paci_c Power and Energy Engineering Conference. pp. 1-4. Shanghai. doi: 10.1109/APPEEC.2012.6306937

[27]. Husmannm, H. J. and Tantau, H. (2001). Integrated optimisation of energy supply systems in horticulture using genetic algorithms. Computers and Electronics in Agriculture. 31 (1), 47-59.

[28]. Mayer, M. J., and Grof, G. (2020). Techno-economic optimisation of grid connected, ground-mounted photovoltaic power plants by genetic algorithm based on a comprehensive mathematical model. Solar Energy, 202, 210-226. DOI: https://doi.org/10.1016/j.solener.2020.03.109

[29]. Vergara, P. P., Torquato, R., and Silva, L. C. P. (2015). Towards a real-time Energy Management System for a Microgrid using a Multi-Objective Genetic Algorithm. 2015 IEEE Power and Energy Society General Meeting, 1-5, DOI: 10.1109/PESGM.2015.7285956.

[30]. Chakraborty, U. (2008). Advances in Differential Evolution. Springer. DOI: 10.1007/978-3-540-68830-3.

[31]. Das, S. and Suganthan, P. N. (2011). Differential Evolution: A Survey of the State of-the-art. IEEE Transactions. on Evolutionary Computation. 15 (1), 4-31. DOI: 10.1109/TEVC.2010.2059031

[32]. Peng, L., Liu, S., Liu, R., Wanga, L. (2018). Effective long short-term memory with differential evolution algorithm for electricity price prediction. Energy. 162, 1301-1314. DOI: https://doi.org/10.1016/j.energy.2018.05.052

[33]. Price, K., Storn, R. M., Lampinen, J. A., (2005). Differential Evolution: A Practical Approach to Global Optimization. Springer. DOI: 10.1007/3-540-31306-0

[34]. Storn, R. and Price, K. (1997). Differential evolution - a simple and efficient heuristic for global optimisation over continuous spaces. Journal of Global Optimization. 11 (4), 341-359. DOI: https://doi.org/10.1023/A:1008202821328

[35]. Suganthi, S. T., Devaraj, D., and Hosimin Thilagar, S. (2015). An Improved Differential Evolution Algorithm for Congestion Management Considering Voltage Stability. Indian Journal of Science and Technology. 8 (24), 1-9. DOI: 10.17485/ijst/2015/v8i24/80243.

Yuvraj Praveen Soni, et. al. “Energy Resource Allocation for a Rural Microgrid: Comparison Using Linear and Nonlinear Optimization Approaches.” *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, 16(6), (2021): pp. 38-47.