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OPTIMAL SIZING OF STORAGE CAPACITY AND DISTRIBUTED GENERATION IN SMART HOUSEHOLDS

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Abstract: In the imminent future, smart grids will enable consumers who invest in distributed generation-battery systems and implement energy management systems to reduce electricity expenses. This study seeks to identify the ideal position and capacity of a customer's distributed generation equipment (e.g., a wind turbine) and battery inside a smart grid framework. The suggested method entails creating an electrical management system that considers stochastic variables, including wind speed, electricity rates, and load demands. A hybrid stochastic approach integrating Monte Carlo Simulation with Particle Swarm Optimisation (PSO) is proposed to attain optimal sizing and position. The PSO method is utilised to concurrently determine the ideal placement and dimensions of the wind generation-battery combination, guaranteeing maximum efficiency and cost-effectiveness. Multiple sensitivity analyses are conducted to confirm the resilience of the proposed strategy across many circumstances, illustrating its efficacy in optimising system performance.

Key Words: Distributed generation, Particle Swarm Optimization, Optimal location and sizing of generators..

I. INTRODUCTION

In order to improve the grid's dependability, the term "smart grid" has come to denote the integration of many technologies such as communication, computation, control, and information.

Efficient, adaptable, and environmentally friendly power grid [1]. Reasons to upgrade to a smarter electrical grid include depleting energy resources, outdated infrastructure, worries about the environment, and rising consumer demands [2]. A more dispersed, adaptive, and predictive power system is anticipated with the arrival of the smart grid, which will impact power system planning, operation, and maintenance.

To get there, we need to build new infrastructure that lets active customers participate, make room for distributed generating and storage alternatives, and include new products and smart control strategies [3].

Smart grids enable two-way communication and power flow, which means that electricity providers and consumers can take advantage of demand-side management [4], real-time pricing [5], power sell-back opportunities [6], etc., to make better use of their assets and save money. Customers of the smart grid of the future could not even be seen as passive loads when it comes to electricity. Customers can become integrated entities that aid the grid by installing smart appliances, storage devices, and distributed energy resources (DERs) that generate electricity, reduce peak demand, increase reliability, and delay investment [7]. The people who use a smart grid will also reap the rewards of these investments.

Investment in renewable generation-battery systems with adequate capacities, for instance, will allow residential consumers to minimise their electricity expenditures. Depending on their resource availability and the current electricity tariffs, they will be able to purchase and store power, which they may then sell back to the grid when they have excess [6]. Residential customers will also be able to employ power management systems to control end-use equipment, which will allow them to modify their loads and transfer portion of them to off-peak hours [8]. Reducing a smart home's power bills is no easy feat; the key is finding the renewable generation-battery system's optimal capacities in relation to the customer's power management system. Electricity rates, the load profile, grid connection policies, and the stochastic behaviour of renewable resources are some of the variables that determine the optimal capacity. Optimal capacity determination for various renewable generating and storage technologies has been the subject of research [9]-[20]. The ideal capacity for independent wind generation-battery systems has been identified by a few studies [9], [10]. Research pertaining exclusively to largecapacity wind turbines has been carried out in a few studies [11-13]. At the same time, studies have been carried out to find the sweet spot for the dimensions of hybrid wind/solar or generation-battery systems, which typically have smaller capacities and can be deployed on the demand side of the grid. Many of these technologies are mainly intended to function in off-grid locations. To power a distant mobile phone base station, for instance, Ekren et al. [16] used a probabilistic method to choose the best standalone solar-wind energy conversion system with battery storage. The problem is that these studies don't give consumers the best possible capacity solution for the smart grid of the future because they haven't included all of the previously mentioned smart home capabilities, such load management and an electricity sell-back option. For the purpose of optimising investments in an DS, Schroeder [21] has introduced a stochastic approach. Nevertheless, the research did not consider the consumer's point of view but rather that of the distribution system operator.

The necessary generation capacity has also been determined in [22] with system reliability in mind. But, electricity prices, demand-side management, or the possibility of smart grid consumers selling power back to the grid are not covered in that research. Power system demand side management has been the subject of several studies [23–27]. While distributed generation and energy storage were not considered in some studies, rule-based expert systems were used for load control [23], [24]. Other demand management systems include stochastic linear programming inside a dynamic pricing scheme [26] and heuristic optimisation methods [25]. Although these methods take electricity tariffs and load types into account when managing demand, they do not take consumers' distributed generation capacities into account. In their analysis of distribution system operators' energy management system costs, Cecati et al. [27] took responsive loads and wind generation into account. That method, however, only addressed an operational issue from a utility standpoint and did not take into account the advantages to specific households.

The primary goal of our research is to find a way to minimise the total electricity cost of a smart house with an electricity management system by determining the optimal capacities of renewable generation (e.g., wind turbines) and battery storage. The following items are included in the study's outcome:

1) A smart home's load-side efficiency and the utilisation of its available facilities and options, such as renewable generation units, storage systems, and electricity transactions with the grid, can be enhanced with a rule-based electricity management system (HEMS).
2) Taking into account the probabilistic behaviour of loads, renewable energy resources, and electricity rates, an optimisation model has been suggested to find the optimal capacities of the smart home's battery storage and renewable generation. This optimisation process makes use of the proposed HEMS. It is also possible to combine additional demand management systems into the presented methodology.
3) To solve the optimisation model and establish the optimal renewable generating and storage capacity of the smart home, an iterative methodology combining a Monte Carlo simulation process with particle swarm optimisation (MCS-PSO) has been developed. In order to solve the optimisation model efficiently, the PSO particles [28] use the iterations in the MCS to capture the long-term stochastic behaviour of a smart home given the expected probability distributions of load, wind generation, and electricity rates.

In order to prove that the suggested approach works, case studies are given. The sensitivity study takes into account a number of factors, including changes in power rates, costs of batteries, and distributed generation.

Although "households" and "homes" are used to simplify the method provided in this paper, it should be highlighted that it is not necessarily confined to residential clients. Actually, by tweaking the input parameters and variables of the suggested model, the procedure can be extended to various kinds of customers with commercial or industrial demands or microgrids in the electricity grid.

II. Requirement of system

Using the problem description as a starting point, the following are some of the study goals:
1. To use Matlab to simulate a network of IEEE 34 buses, containing a number of weak buses. Second, to use the PSO approach to determine the best size and location for the DG units in this power network.

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2. To suggest a better PSO approach for the altered power network's optimal DG unit size and location.

3. To compare the two methods and demonstrate how the proposed method is superior.

III. Test system implementation:

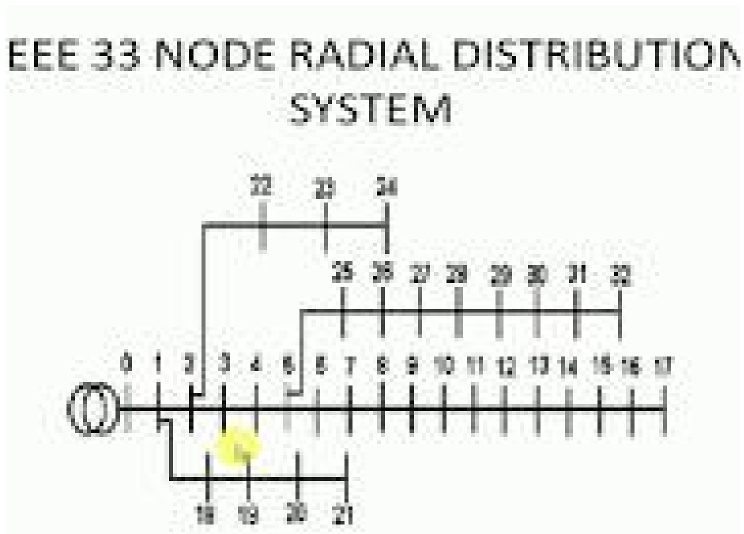

Figure 1 IEEE 33 bus system

a) Diffusion of Power Sources

Knowing the type and technology of DGs is crucial for selecting the appropriate type according to the grid's situation. To clarify, there are varieties of DGs that can be categorised as conventional based DGs, and they do not rely on renewable energy sources. The following are some categories under which DG kinds and technology fall. Old-fashioned power plants that use combustion engines, including microturbines (MT). In order to generate electricity, these turbines transform the kinetic energy that is derived from heat. According to El-Khattam and Salama (2004), the most common fuels used to provide heat through burning are gas, oil, and coal.

2-Generators that don't follow the conventional model and rely on renewable energy sources [El-Khattam and Salama, 2004]. Fuel cells (FCs) and other electrochemical devices, as well as photovoltaic (PV) and wind turbine (WT) power systems, are examples of these generators. Memory devices such as batteries, flywheels, and ultra-capacitors!

Micro-turbines, One kind of DGs that uses combustion is the micro-turbine, or MT. It might be thought of as a classic variety. Compact combustion turbines are known as MTs.

b) Sizing and Location Using PSO

Optimal DG sizing and placement can be achieved using PSO, one of several meta heuristic optimisation approaches. One way to look at PSO is as a computational approach that finds the best answer to a problem by repeatedly adjusting the answer based on certain constraints. Algorithm attempts to focus on a specific location to refine a proposed solution. Incorporating these two ideas, swarm particles use their memories to search for the best possible solution, saving information like their personal optimal position and the swarm's global optimal position. Every particle in PSO's search space has a global best position, a local best position, a velocity, and a solution and fitness. Particles are the individual components of a swarm. The particles swarm together, each with its own unique set of coordinates in three dimensions. The fitness function, also known as the objective function, is what bridges the gap between the ideal and physical problems and establishes how well a solution fits the former. Every iteration updates two terms in the search space. One is the optimal location in the search space as returned by the fitness function for a given point t.

However, the second one represents the optimal location in the search space as returned by the fitness function for the entire swarm. Constraints can also take the form of upper and lower bounds on the velocities of the particles moving across the search space [Abugri and Karam, 2015].

In PSO, each particle is represented in a d-dimensional space, where

$$x_i = \left(x_i^1, x_i^2, \dots, x_i^n\right), \quad V_i = \left(v_i^1, v_i^2, \dots, v_i^n\right)$$

represents the position and velocity of i^{th} particle, respectively

$$v_{i+1} = \omega V_i + c_1 r_1 (P_{best} - x_i) + c_2 r_2 (G_{best} - x_i)$$

where:

r1 and r2 two random variables in the range of zero to one

c1 and c2 positive constants which determine how far the PSO particles move toward P_{best} and G_{best}

ω: the inertia weight.

$$x_{i+1} = v_{i+1} + X_i$$

The convergence is controlled by inertia weight (ω) which is chosen at suitable way so as to give a good balance between global and local exploration. Here, if ω ≥ 1, the velocities increase with time and PSO diverges, while, if 1 > ω > 0, PSO converges.

The following are the main steps of the algorithm depicted in figure 3.4, which illustrates the PSO method: [Eberhart and Kennedy, 1995]:

1.initialisation, which is when all the setup is set up, including the distributed network's setup, potential DG size and placement candidates, a randomly generated beginning population, an appropriate amount of repetitions, and lastly, the objective function, together with a randomly generated velocity and position.

2. Fitness function calculation:following program start in the within the search space, the fitness function determines the total of all particles.

3.P_{best} and G_{best} at each iteration, the population's t is computed. Named after the iteration's lowest fitness value. Also recorded is the difference between the current value and the value from the previous iteration.

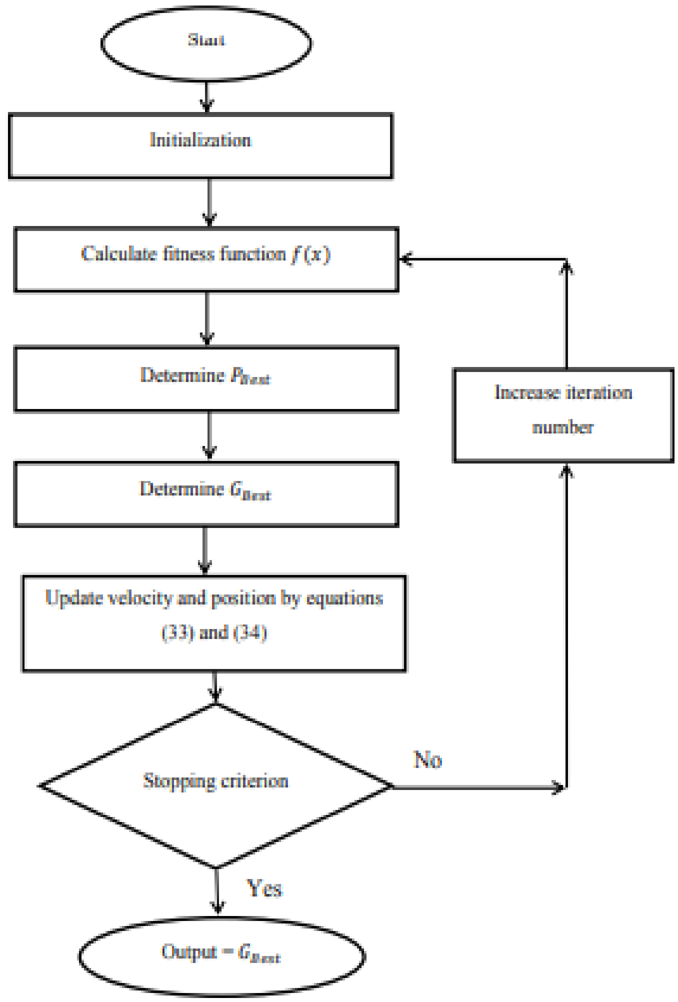

Figure 4 Standard PSO algorithm

4. In order to determine the new position and velocity for the following iteration.

5. Refreshing the new position is the fifth step.

6. If the condition was successful in achieving the given accuracy, the algorithm returns to step2.
7. At last, the ideal or target result is defined as G_{best}.

c) A Home Energy Management System Based on Rules Section

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Home Electricity Management System Based on Rules (B) Get the most out of your smart home's features with the help of HEMS's two sets of decision rules. The primary set of regulations controls the primary storage system's Task 1, as well as the total production and consumption of power in the house.

Electricity rate, generation, and load statistics are collected first in this application. The guidelines are then put into play in order to reduce the customer's power bill to a minimum. Decisions to drain the battery or purchase power from the grid are made under this scheme if generation falls short of meeting the overall load. If this does not happen, the excess power will be sent back to the grid or saved for later use. Each period's remaining battery charge is carried over to the next one.

IV. MATLAB Test Results

Case – 1:

By analyzing for two DG's sizing and location in IEEE 33 bus system

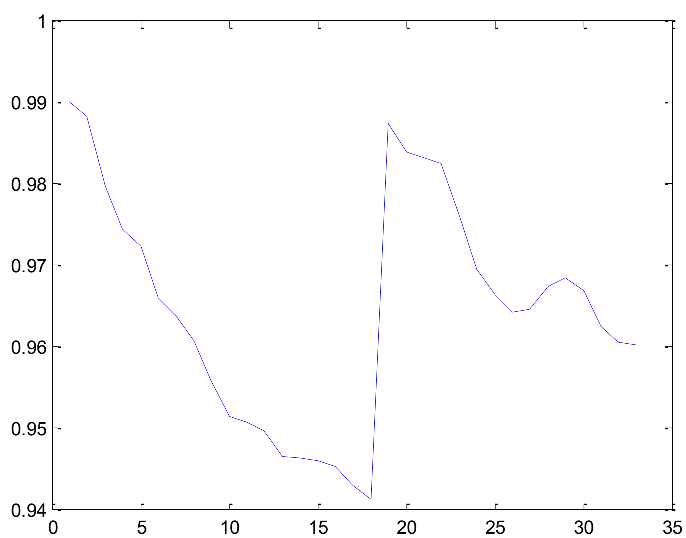

Figure 5 Swarm movement curve

Elapsed time for calculation is 87.666268 seconds.

Power loss estimation

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Power-Loss= 9.722534e+001 KW

Power-Loss= 6.407375e+001 KVAr

DG Location:

DG1 Location= 33

DG2 Location= 18

DG sizing

DG1 Power = 9.086391e+002 KVA

DG2 Power = 9.340771e+002 KVA

Case – 2:

, By analyzing for one DG's sizing and location in IEEE 33 bus system

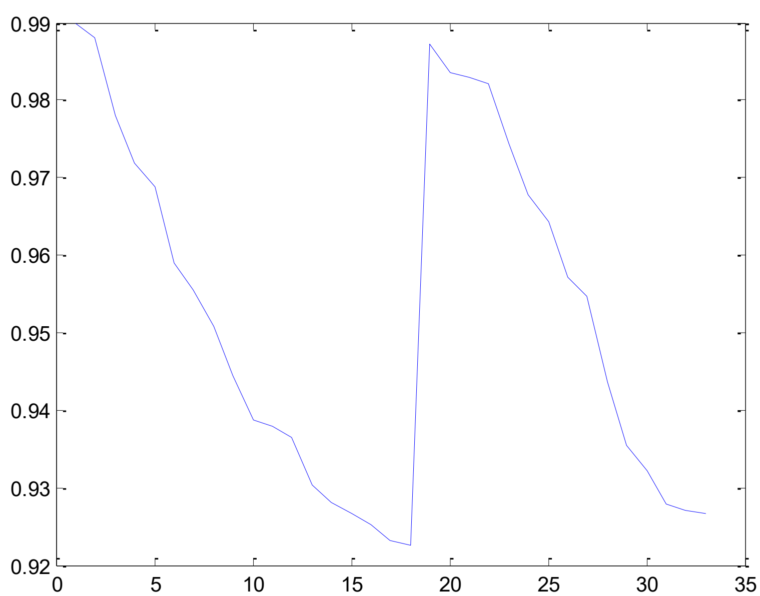

Figure 6 Swarm movement curve

Elapsed time for calculation is 50.349161 seconds.

Power loss estimation

Power-Loss= 1.468539e+002 KW

Power-Loss= 9.949003e+001 KVAr

DG Location:

DG Location= 33

DG sizing

DG Power = 1.866815e+003 KVA

IEEE 33 bus system Loss analysis data

Sr	Plosskw	Qlosskw	voltage
1	4.862579431	2.478755241	0.99
2	23.99598524	12.22189025	0.988305635
3	12.45017065	6.340742647	0.9796591
4	4.087131442	2.081637924	0.974519127
5	8.149134814	7.034723215	0.972342745
6	0.722521689	2.388335583	0.966041446
7	2.304771349	0.761669587	0.964009551
8	2.752372129	1.977432403	0.960826961
9	2.329147232	1.650928115	0.955956438
10	0.338035662	0.111761536	0.95147391
11	0.476785392	0.157654999	0.95083306
12	0.83837161	0.65961799	0.949781167
13	0.002327772	0.003064011	0.946617933

14	0.01448768	0.01289428	0.946484025
15	0.077133348	0.056328118	0.946127532
16	0.307768144	0.410914644	0.945355966
17	0.412572737	0.323520152	0.943016009
18	0.263952252	0.256453609	0.941333473
19	0.847803157	0.763935912	0.987447897
20	0.102651296	0.119922784	0.983863694
21	0.044454865	0.058777748	0.98315833
22	3.207187697	2.191436097	0.982520475
23	5.185294067	4.094534547	0.976138517
24	1.297907142	1.015583367	0.969593684
25	2.487939229	1.267255745	0.966337504
26	1.26209775	0.64259516	0.9642537
27	5.455208871	4.809753091	0.9646359
28	7.485715592	6.521378194	0.967388272
29	3.722681525	1.896183594	0.968548035
30	1.524601285	1.506764201	0.966924605
31	0.203951867	0.237713948	0.962607157
32	0.012597304	0.019586776	0.960590652
33	97.22534022	64.07374547	0.960328762

V. Conclusion

The suggested hybrid stochastic approach finds the best size and placement for smart grid-integrated distributed generation-battery systems. The method allows for a more precise and adaptable energy management system by taking into account random variables like wind speed, power rates, and load. Investors in distributed generating systems can enjoy better efficiency and lower electricity prices because to PSO's integration, which optimises both location and size simultaneously. If you want to be sure you can use the method in any situation, the thorough sensitivity analyses show that it works well even when the conditions change.

Smart grids have the ability to improve energy efficiency and dependability by supporting distributed generation and battery systems, according to this study's conclusions. Through careful optimisation of system capacity and placement, the suggested strategy has the potential to significantly impact the trajectory of decentralised energy management going forward. This approach paves the way for a more sustainable and cost-effective energy environment by providing customers and grid operators with a practical and scalable alternative to improve demand-supply balance.

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