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Demand Side Response with Optimized Economic Load Dispatch using Particle Swarm Algorithm

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Abstract: Electrical power systems are designed and operated to meet the continuous variation of the required load demand. The literature surveyed mostly reported optimized demand response with economic dispatch without considering customer incentives for power transferred to the grid. This study seeks to explore the efficacy of evolutionary swarm optimization technique, the particle swarm optimization (PSO) to validate the optimum choice of distributed energy sources in microgrid demand side response with customer incentive-based economic load dispatch (ELD). The results indicate the cost of the grid power is directly proportional to the energy supplied and inversely proportional to the transferred energy, energy received and the customer incentives. The solar energy ($\boldsymbol{P\_s}$) and wind ($\boldsymbol{P\_w}$) supplied for hours complemented the grid supply and increased the customer incentives from \$5.5 to \$36 per kWh representing over 18% improvement and reduced the corresponding grid intake from 360 kWh to 317 kWh representing about 14% decrease. Future work on this demand side response with ELD should include additional optimization techniques and larger solar PV and wind energy powers to validate the efficiency in a more complex microgrid.

Keywords: Customer incentives, demand side response, distributed energy resources, economic load dispatch, Particle swarm optimization

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1. INTRODUCTION

Electrical power systems are designed and operated to meet the continuous variation of the various load demand. It is the catalyst for industrialization, enhancing communication, fostering inventions in science and technology, ensuring effective healthcare delivery, and elevating citizens' standard of living. In power system optimization, minimizing operational costs is crucial for prioritizing optimal investment decisions. The economic load dispatch (ELD) of electrical energy generation section has consistently played a significant role in the electric power sector [1].

ELD is a computer-based procedure that allocates the entire required generation among operational generating units by minimizing a chosen cost criterion, while adhering to load, operational, and power limitations. Under specified load conditions, ELD computes the power output of each plant and its individual producing units to optimize overall fuel expenditures necessary to satisfy the system load [2]. To allocate the overall output among the accessible units, ELD is used in real-time energy management and control in power system by several applications. ELD places an emphasis on the system-wide allocation of production cost estimation for all power units. It is fundamentally an optimization problem focused on reducing the overall generation cost of generation while complying with constraints [3]. Prior endeavors to tackle economic dispatch (ED) challenges have encompassed various mathematical programming approaches and optimization techniques. Traditional methodologies include the lambda-iteration, the base point and participation factors and the gradient methods [4].

The combine generation-grid-load ED incorporates the flexibility of both the transmission and demand sides in conventional power generation dispatch, treating the transmission grid structure and load power demand as adaptable resources available for dispatch [5]. The transmission and demand sides are incorporated into the dispatch technique of power generation via adjustments in power grid configurations, utilizing market incentive mechanisms such as price signals or demand response to establish an integrated economic dispatch model that facilitates the interaction of transmission, generation and utilization, thereby achieving the optimal global configuration of generation, on-grid and demand load [6].

Demand response (DR) comprises two elements: tariff-based and incentive-based instruments designed to motivate energy consumers to react to fluctuations in electricity prices or to receive incentives for decreasing the grid power use. The primary concept of price-based demand response is to incentivize electricity consumers to capitalize on fluctuating electricity prices by shifting loads to periods of low demand. Demand-side response (DSR) utilizes load flexibility to enhance the effective functioning of the power system management. The flexible load from home consumers, such as heating elements, can be rescheduled for periods of minimal demand, thereby enhancing system performance and enabling Service Operators (SO) to arrange an appropriate energy mix at minimal operational costs. Flexible or variable demand is described as the capacity to change the load consumption profile by adjusting power usage, operational timing, and the activation schedule of electrical devices [7].

Conversely, the incentive-based DR provides customers with additional incentives beyond their retail power cost for reducing demand on flexible loads during periods of required system reliability or elevated electricity prices.

The categories of DR based on incentives include

i. Direct Load Control (DLC).
ii. Interruptible service.
iii. Demand bidding or buyback.
iv. Emergency Demand Response Program (EDRP).
v. Capacity market program.
vi. Diverse auxiliary service market.

Furthermore, recently the attention of SO has mainly been on renewable energy penetration (RF) on the supply side. However, the demand side (DS) energy management strategy is also characterized by customer attitude to power consumption. Many research were carried out with hope of arriving at standard model for power consumption behavior change to take care of the stochastic nature of the renewable energy sources (RES) [8]. The fundamental operational constraints include the power balance constraint, which mandates that the total generated power equals the load demands plus the transmission losses in the microgrid, and the limitations of power supply which require individual generator units to operate within their designated power range.

The particle swarm optimization (PSO) method is an evolutionary optimization tool initially conceived by Eberhart and Kennedy in 1995. It is a swarm intelligence-based domain predicated on swarm population, wherein every member of the swarm is regarded as a distinct particle, hence each individual particle is considered as a solution to the pertinent problem. The particles possess a randomized velocity that traverses the problem search space. In contrast to genetic algorithms (GA), PSO lacks operators like mutation and crossover. The PSO does not display the survival-of-the-fittest phenomenon; it solely employs the imitation of socially exhibited behavior [9]. It also, however, allows each particle to remember the memory of the previous optimum solution that it has found as well as the current best solution found in the neighborhood particles.

This paper is aimed at providing a means of distributing the power demand and minimize network losses among different DERs of wind turbine (WT) and solar Photovoltaic (PV) integrated into microgrid. This work uses a famous evolutionary optimization technique PSO algorithm to optimize the objective of minimizing the levelized cost of energy considering the loss of power supply probability reliability constraint. The energy mixed consists of PV WT and the grid. To determine the right size or the least cost of energy while the loss of power supply probability reliability index is constraint [10].

The significance of this research on the ELD became necessary because of the importance of effective load dispatch on the quality and reliability of power supply system generally and also for the following objectives:

i. To ensure minimum loss in both transmission and distribution.
ii. To provide an effective and optimum scheduling of the generators.

Unfortunately, generating units' input-output characteristics are naturally quite nonlinear because of valve-point loadings, which is one of the major drawbacks of distributed generation [11]. The non-smooth optimization problem with equality and inequality constraints is the practical ELD problem in addition to the valve-point effects. This renders the quest for the global best solution arduous. The dynamic programming (DP) method is a methodology for addressing the non-linear and discontinuous ELD problem; nevertheless, it is hindered by the challenges of "curse of dimensionality" and local optimality [12].

1.1 Power Flow Analysis

Power flow studies, also referred to as load flow analysis, constitute the foundation of power system evaluation and design. It is essential for operation, planning and economic scheduling, and power exchange among utilities. Furthermore, power flow analysis is essential for various other evaluations, including contingency studies and transient stability. There are three popular power flow solution techniques, which are Gauss Seidel, Newton Raphson, and Fast decoupled methods [13].

Load flow methods usually consider four main factors: voltage magnitude and angle, active power (PV) and reactive power (PQ) across different bus types (PQ, PV, and droop buses), and voltage angle. Some factors are known, but others are not known. In a PQ bus, while the active and reactive power values are known but not the voltage angle or magnitude. On the other hand, the voltage and active power values in a PV bus are known. In a droop bus, all factors are regarded as unknown. Therefore, method was devised for load flow analysis, consisting of two separate loops: the main (secondary) loop and the internal (primary) loop. The primary loop is tasked with identifying the optimum solution of the designed objective function, whereas the secondary loop is designated for load flow calculation [14].

1.2 Economic Load Dispatch

The ELD refers to the allocation of generation levels to generating units to ensure complete and cost-effective supply of power to the system load. Minimizing generation costs is essential for an interconnected system. Solar PV and wind power plant technologies are gradually progressing and attracting increased global attention. Several renewable energy sources (RES), such as solar PV and wind power, demonstrate a strong generating capacity that varies over time (variability) and is weather dependent therefore, not entirely predictable (due to uncertainty), unlike conventional energy sources.[15]. The economic load dispatch determines the generation capacity of each plant to minimize generation and transmission costs for a certain operational schedule.

The main goal of an ELD-based problem is to get the objective function as minimum as possible. The objective function of this work was being designed to be the total cost of production of the power that meets the demand and all other limits. The ELD finds the optimal combination of power generation that minimizes the total fuel cost while satisfying the total demand subjected to the operating constraints of a power system with a defined interval [16].

The aim of ELD is to reduce the total generation cost. The economic load dispatch strategy for generating units at varying loads must minimize total fuel costs. In a conventional power system, numerous generators are employed to deliver sufficient overall output to meet a specified consumer demand. Each producing station typically possesses distinct cost-per-hour attributes for its operational output range. The ELD uses the well-known classical set of coordinating equations. These equations were generally solved by iterating the value of the LaGrange multiplier until the sum of the generator outputs equals the system demand plus the transmission losses.

On the other hand, ELD is used to solve difficulties including planning the expansion of power system generation, reconfiguring distribution networks, and identifying generator parameters. Researchers in the field of power engineering have long recognized the planning of power system generating expansion as a challenging optimization problem [17]. Reliability, security, and other system requirements must be met while lowering the total expenses.

1.3 Optimization Technique based on PSO

Swarm intelligence is a relatively new area of study that focuses on how groups of people might learn to work together more effectively. Swarm intelligence, like that of social insect societies or bio-inspired technique, takes its cues from the way in which each member of the group uses their unique set of experiences to ensure the group's survival. Increasing its resilience in the face of opposition. Ant colonies' food-searching activity, immune systems' foraging, and bacteria's foraging are some of the most commonly used examples of swarm intelligence [18].

In principle, each particle in the swarm can use the previous experiences and discoveries of every member of the swarm during search for forage. The primary objective of creating PSO is as a result of hypothesis positing that the interchange of information between members of the same swarm species confers certain evolutionary advantages. PSO is typically defined as a straightforward heuristic with a well-balanced mechanism, possessing the ability to improve and conforms to both local and global exploration capabilities. It is a stochastic search method which is computationally efficient and simpler to implement than other metaheuristics techniques. It uses a group of points to look through the search area, just like other population-based algorithms. Each member in the swarm is called a "particle" and represents a possible answer. Each particle makes decisions based on two important types of input. Previous experience of a particle which informed the choice and the quality of the chosen option [18,14].

Thus, each particle in PSO monitors its position in the problem search space corresponding to the optimal solution (greatest fitness) it has attained to date. The term is referred to as *pbest*. The global version of the PSO monitors the overall best value and its corresponding position achieved by any individual within the population thus far. This site is referred to as *gbest*. Each particle alters its position within the search arena and adjusts its velocity based on its individual experiences and those of its neighbors. Flight discoveries towards *pbest* and gbest destinations and global variant of PSO. Acceleration is influenced by the stochastic generation of members directed towards pbest and *gbest* locations, respectively.

1.4 Contributions of the Paper

This study seeks to explore the efficacy of evolutionary swarm optimization technique to validate the optimal choice of distributed energy sources in microgrid demand side response. Specifically, the study seeks

i. To investigate the utilization of Particle Swarm Optimization (PSO) in demand-side response to enhance the selection of distributed energy resources (DER) for the purpose of maximizing customer savings.
ii. To evaluate that the increase in renewable energy (RE) penetration in microgrids results in significant incentives for subscribed customers.

2. LITERATURE REVIEW

The PSO when juxtaposed with classical optimization techniques, confirmed to demonstrates greater versatility and applicability in complex computations compared to modern heuristic optimization algorithms derived from operational research and artificial intelligence concepts, such as simulated annealing (SA), artificial neural networks (ANN), and tabu search (TS). In an elaborate attempt to propose optimum demand response programs, the authors in [19] proposed emergency demand response program (EDRP) predicated on consumer response to higher power costs and the incentives provided by Independent System Operators (ISOs) during peak hours.

However, [20, 21] developed an innovative incentive-based demand response algorithm in real-time for smart microgrid systems utilizing deep neural networks and reinforcement learning, designed to assist the service provider in procuring energy resources from subscribed users to mitigate energy fluctuations and improve microgrid stability. To address future uncertainties, a deep neural network was employed to forecast unknown pricing and energy consumption. In related study [10] proposed simulations performed for two primary types of demand response program (DRP) incentive-based programs and time-based programs, utilizing an 11-bus microgrid over a 24-hour period and a 14-bus microgrid over a 336-hour period (two weeks). The findings demonstrated the impact of DRPs on overall operational expenses, customer advantages, and load profiles, while also identifying the optimal utilization of energy resources in microgrid operations.

Nonetheless, research on ELD incorporating demand-side response that comprehensively considers the flexibility of both microgrid load demand and generation constraints is rarely undertaken [22]. This paper presents an economic dispatch strategy for generation, optimized incentive to subscribed customers and load that integrates demand response. Expanding upon existing research by incorporating the optimization of customer savings and microgrid power architecture with demand response on the load side.

3. METHODOLOGY

This study primarily examines two mechanisms for demand response: interruptible load and electrical demand incentive. The attributes of wind and solar energy provide anti-peak control, optimizing electricity generation and consumption via an interruptible mechanism of peak load demand [23]. Additionally, price incentives can be employed to increase electricity demand and mitigate wind and solar curtailment during valley load periods [24]. Figure 1 shows how the problem formulation procedure of the optimization tool was outlined considering the renewable energy sources and the grid profiles.

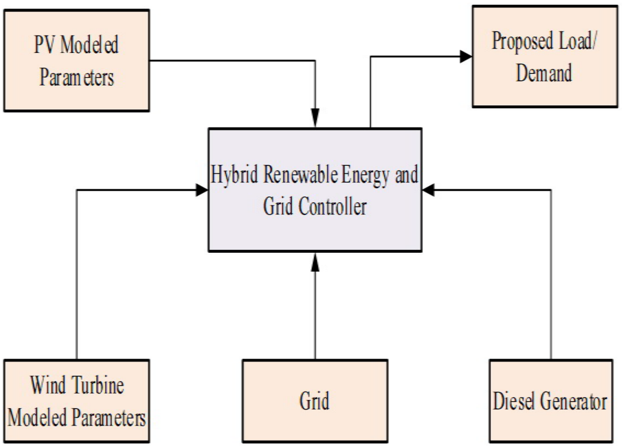

Figure 1. Typical Configuration of Hybrid Microgrid

In this scenario, due to the rising integration of large-scale wind and solar power utilization, the electrical power generation and supply of conventional thermal power struggles to align with power balance in real-time [25]. Therefore, it is essential to maximize the regulatory ability of renewable power sources, microgrid networks and electric load sides within an economic dispatch framework. The data for wind turbine modelling and solar PV profiles are obtained from [26]. while that of generators G1, G2 and G3 are reused from [27].

This study evaluates the efficacy of the proposed PSO-integrated DERs approach through three case studies including generators G1, G2, and G3 all considered as grid focusing on the objective functions to determine the generator with minimal operating costs and maximal customer incentives based on transferred power. The PSO effectively managed the restrictions of power balance and scheduling, while coordination was accomplished without accounting for network losses as shown in appendix A.

The RE sources are balanced with the respective customer demand side profile. The grid supply is only taken when the RE sources couldn't meet the load demand of the particular customer [28]. At the same time, when the RE energy sources have excess supply, it could be taken by the grid and monetized as incentive during billing by SOs. Figure 2 shows the solar PV, wind powers as RE sources and the three generators as grid.

All simulation programs and codes were executed on a Dell Latitude E5570 laptop equipped with an Intel(R) Core i5-6300U CPU operating at 2.40GHz and running Microsoft Windows 10 Pro. The application and simulations were executed using the MATLAB R2023b software package.

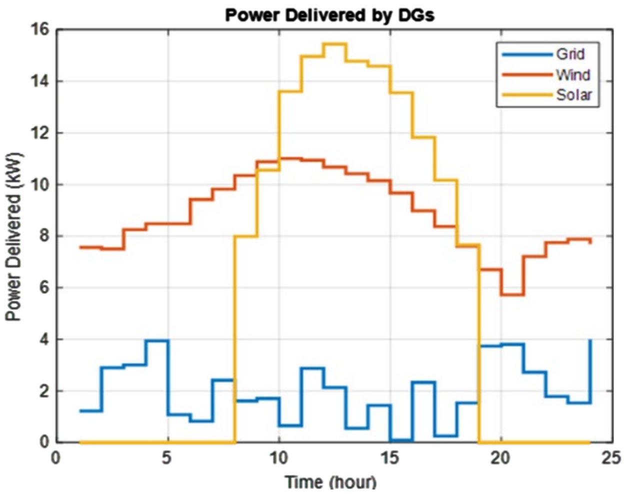

Figure 2. Renewable energy sources and grid profiles

3.1 Problem Formulation

The Unit Commitment problem has ED as a component. In practice, even though the planned combination units for each operational period are defined. The ED planning has to find out the best way to separate up the generation among the active units to meet the system's load demand and the spinning reserve capacity, and generators' operational constraints, such as ramp rate limits and not allowed operating zones [29]. The ELD problem aims to determine the optimal mix of power generation that minimizes total costs while meeting overall demand and adhering to system restrictions.

The interruptible load reduces the active power production of traditional generators with high marginal costs to achieve the optimal overall benefit of power generation and consumption during peak load periods. The demand for electricity is augmented through pricing incentives to enhance the use of clean power generated by wind turbine and mitigate wind curtailment during periods of low load period [30]. The following assumptions within the mathematical models are structured as follows.

i. Solar PV and wind power energy generation is not schedulable. Consequently, the SO must mandatorily utilize all available generation from these sources.
ii. Renewable generation and system load predictions are presumed to be accessible at three days intervals between the three consecutive cases of economic

ED.

iii. The generators at the preceding step of ED are presumed to be identified, to verify generation constraints compliance at this level.

iv. The model schedule time is 24 hrs. and divided into hourly intervals and three randomly selected days of the year were used as CASEs 1, 2 and 3.

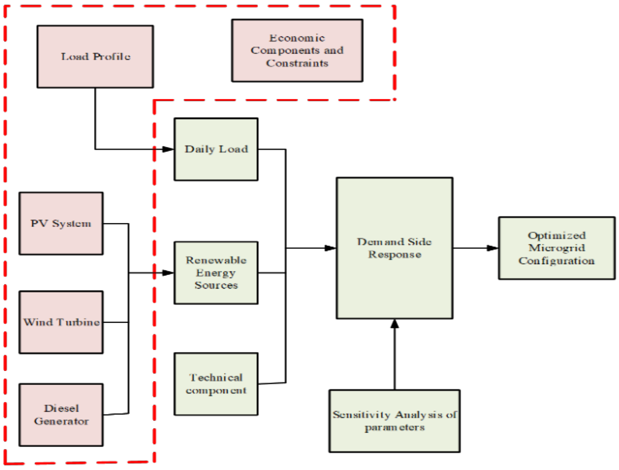

Figure 3. Optimization Problem Formulation Procedure

The goal of ELD is to keep the total cost of running the system as low as possible, considering the limits of power production or generation constraints [31]. Figure 4 shows the power delivery sequence by the various generators

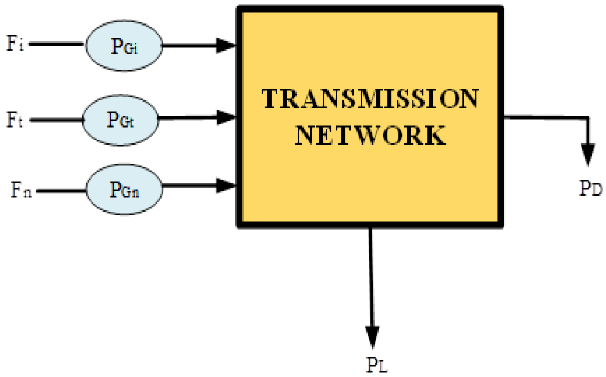

Figure 4. Power delivery sequence by generators

$F_{i\ t\ n}$ is the cost of fuel in unit $i\ t\ n$

P_{Gi} is the delivered power by unit i

P_D is the demand power total

P_L is the total losses in power

Figure 3 shows the optimization problem formulation of the microgrid with DSR. The quadratic cost function of a unit that is obtained from Equation (1).

$$F_i(P_{Gi}) = \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 \quad (1)$$

αi is the coefficient of constant cost of unit
βi is a coefficient of linear cost unit and
γi is the coefficient of quadratic cost unit

To keep the running cost of the various generators to the lowest possible minimum, mathematically formulated as shown in Equation (2).

$$F_T = \sum_{i=1}^{n} F_i(P_{Gi}) \quad (2)$$

F_T is a generation total cost
$F_i(P_{Gi})$ is a cost of generation at unit i

The inequality constraint condition shows the minimization of the model as shown in Equation (3).

$$\sum_{i=1}^{n} PGi = PD + PL \quad (3)$$

The generator injected power *PGi* is the sum of the demand power *PD* and the line power losses *PL*. Considering *B*-coefficient technique, the losses in the network are expressed in Equation (4)

$$P_L = P_{Gi}^T \, B \, P_{Gi} \quad (4)$$

Hence, the loss coefficient is given as B Inequality Constraints is shown in Equation (5).

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \quad (5)$$

Thus P_{Gi}^{min} is the lowest power limit of unit *i* and
P_{Gi}^{max} is the highest power limit of unit *i.*

When selecting the wind turbine and solar PV simulation models [32]. The power output of a wind turbine is primarily influenced by three factors: the power output curve (determined by avionics power, electromechanical transmission, and electrical conversion efficiencies) of the specific wind turbine, the wind speed distribution at the installation site, and the height of the tower.

The wind power is modeled as in Equation (6).

$$V = Vr\left(\frac{Wwt}{Hr}\right)\alpha \quad (6)$$

The *V* represents the wind speed at the height of the wind turbine (HWT) in m/s; Vr denotes the wind speed recorded at the reference height (*Hr*), and the height parameter α is the wind speed power law coefficient.

The maximum power output delivered by the solar PV can be obtained from Equation (7).

$$P = FF \text{ x } Voc \text{ x } Isc \quad (7)$$

Where *FF* is the field factor; V_{oc} is the open circuit voltage I_{sc} is the short circuit current. I_{sc}, V_{oc}, *FF*, and P_{max}, as functions of solar irradiation intensity and module temperature, are the four essential electrical parameters of a photovoltaic module that are pertinent to this design.

3.2 Objective Function Formulation

To combine the two limitations into an ED issue, the restricted optimization problem for a specified operating period can be reformulated as in Equation (8).

$$\min(Fi) = \sum_{i=1}^{m} Fi(Pi) = \sum_{i=1}^{m} \alpha i + \beta i Pi + \gamma i Pi \quad (8)$$

i. Power balance constraints

$$\Sigma Pi = PD + PL, \; i=1,\ldots\ldots, m \quad (9)$$

ii. Generator operation constraints

$$\max(Pi^{min}, P^{o} - DRi) \leq Pi \leq \min(Pi^{max}, P^{o} + URi) \quad (10)$$

iii. Line flow constraints

$$/P_{LF,k}/ \leq P_{LF,k}^{max}, k = 1, \ldots, L \quad (11)$$

Whereas the cost function of the generation *Fi(Pi)* is represented as a quadratic polynomial, where *m* signifies the number of generators engaged in the operating system. *Pi* represents the output power of the ith generator, whereas $P_{LF,k}$ denotes the real power flow of line *j*, with *k* indicating the number of transmission lines. The total network losses of the transmission lines were a function of unit power output represented by Equation (12).

$$P_L = \sum_{i=1}^{m} \sum_{j=1}^{m} Pi\beta ijPj + \left(\sum_{i=1}^{m} BoiPi + Boo\right) \quad (12)$$

4. RESULTS AND DISCUSSION

The PSO efficiently handled the constraints of power equilibrium and scheduling, while coordination was executed without consideration of network losses. The RES are aligned with the corresponding consumer demand profile. The grid supply is utilized solely when RES fail to satisfy the specific customer's load requirement. Simultaneously, when RES generate surplus supply, it can be absorbed by the grid and monetized as an incentive.

Figure 5 indicates the utilization of 194.79 kW of solar PV, 135.21 kW of wind powers and grid supply as CASE 1. The total grid supplied energy under this scenario is 360.08 kWh and the total energy absorbed by the customer is 175.86 kWh as can be seen from Table 1.

Table 1. CASE1 Renewable Energy Power of 330 kW

CASE 1 with total RE 330 kW	
Total Grid Power Cost ($):	206.1486
Total Transferred Power Cost ($):	211.4772
Total Customer Incentive ($):	1055.8424
Total Customer Energy Received (kWh):	127.8418
Total Grid Energy Supplied (kWh):	360.0801
Total Transferred Energy (kWh):	48.0175

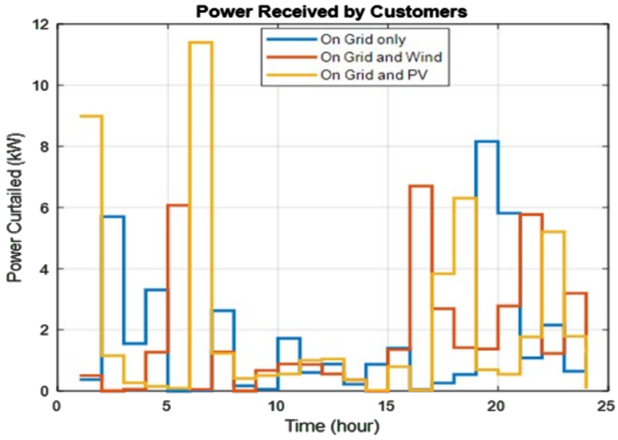

Figure 5. Total received power by customer in CASE 1

This translates to only 48.61% of the generated energy has been used under this scenario with RE penetration incentives of 2.5% savings as shown in Figure 6.

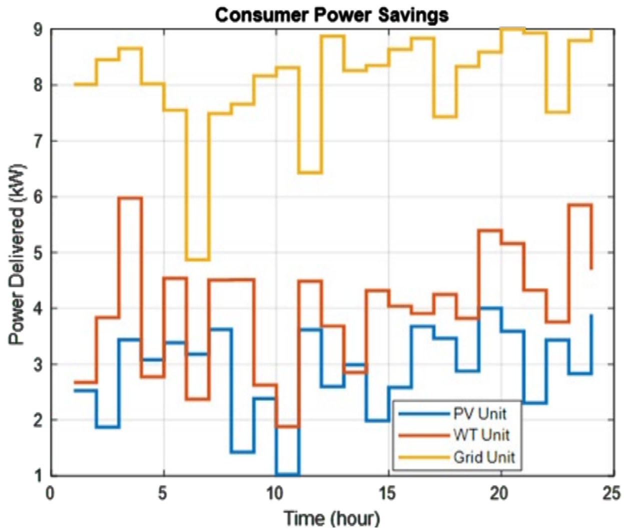

Figure 6. Demand side customer savings in CASE 1

Figure 7 illustrates the absorption of 180.62 kW from solar PV sources, 242.52 kW from wind energy, and grid supply, designated as CASE 2. The total energy supplied by the grid in this scenario is 345.59 kWh, whereas the total energy consumed by the customer is 195.20 kWh as shown in Table 2.

Table 2. CASE 2 Reenewable Energy Power of 423 kW

CASE 2 with total RE 423 kW	
Total Grid Power Cost ($):	195.7598
Total Transferred Power Cost ($):	159.7161
Total Customer Incentive ($):	1102.2767
Total Customer Energy Received (kWh):	150.717
Total Grid Energy Supplied (kWh):	345.5927
Total Transferred Energy (kWh):	44.4805

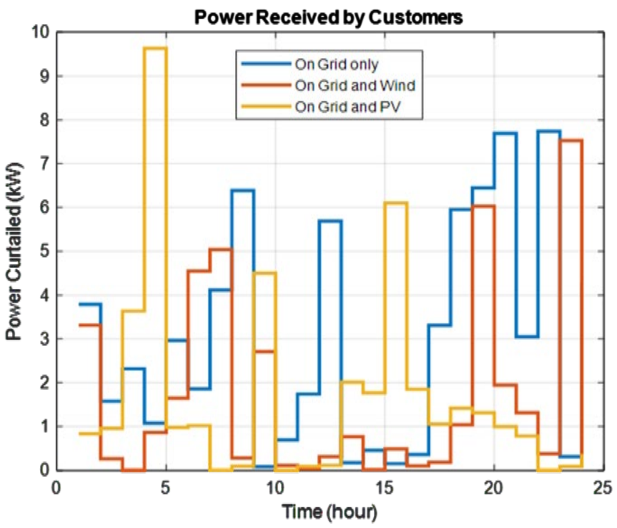

Figure 7. Total received power by customer in CASE 2

This indicates that only 43.52% of the produced energy has been utilized in this scenario, with renewable energy penetration incentives yielding up to 22.56% savings, as illustrated in Figure 8 and Table 2.

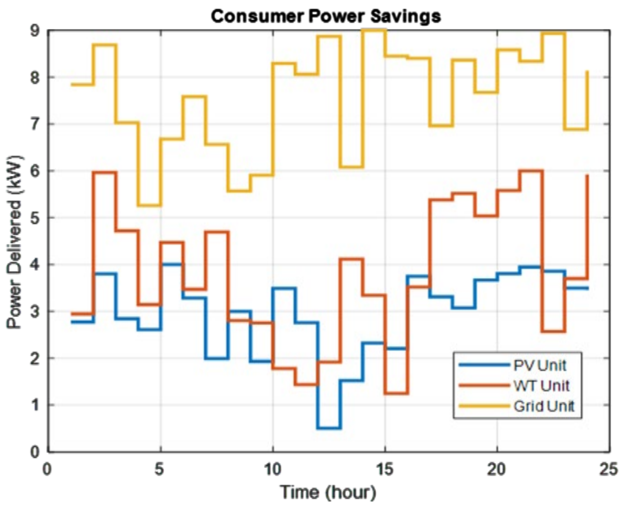

Figure 8. Demand side customer savings in CASE 2

Figure 9 shows the integration of 200.49 kW from solar photovoltaic sources, 278.71 kW from wind energy, and grid supply, designated as CASE 3. The total energy supplied by the grid in this scenario is 317.48 kWh, whereas the total energy consumed by the customer is 205.37 kWh as shown in Table 3.

Table 3. CASE 3 Reenewable Energy Power of 479 kW

CASE 3 with total RE 479 kW	
Total Grid Power Cost ($):	174.8693
Total Transferred Power Cost ($):	140.0397
Total Customer Incentive ($):	1303.574
Total Customer Energy Received (kWh):	165.8875
Total Grid Energy Supplied (kWh):	317.2828
Total Transferred Energy (kWh):	39.4805

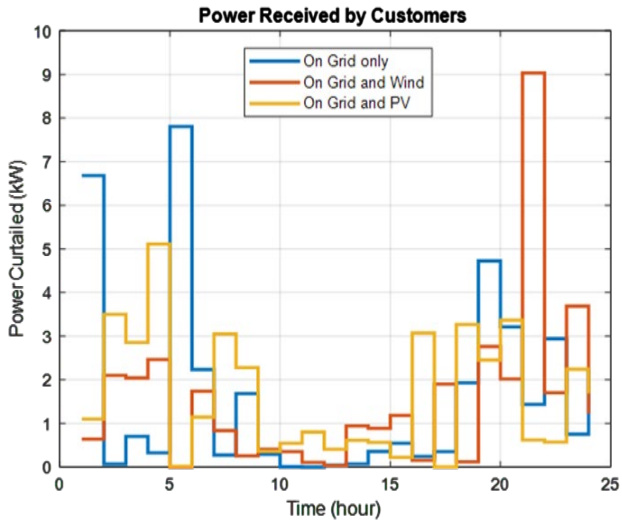

Figure 9. Total received power by customer in CASE 3

This increase in kWh illustrates that only 35.31% of the generated energy has been utilized in this scenario, with renewable energy penetration incentives of 24.87% savings, as shown in Figure 10 and Table 3.

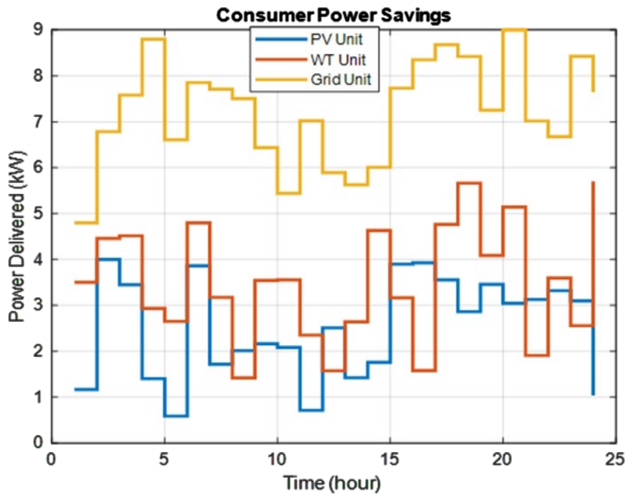

Figure 10. Total received power by customer in CASE 3

The increase in renewable energy sources integration from 300 to 479 kW reduced the power absorbed from the grid from 49% to 35%, a marginal decrease of 14%. However, the demand side customer incentives also increased from 2.5% to 24.87% a marginal increase of over 22% as shown in the summary Table 4.

Table 4. Summary of total power delivered by RE DGs

	Case 1	Case 2	Case 3
Total grid power cost ($):	206.15	195.76	174.87
Total transferred power ($):	211.48	159.7	140.04
Total customer incentive ($):	1056	1102	1304
Total Energy Received (kWh):	127.84	150.72	165.89
Total energy supplied (kWh):	360.08	345.59	317.48
Total Transferred Energy (kWh):	48.02	44.48	39.48

5. CONCLUSION

The cost of the grid power is directly proportional to the energy supplied and inversely proportional to the transferred energy, energy received and the customer incentives. The solar energy (P_s) and wind (P_w) supplied for hours complemented the grid supply and increased the customer incentives from $1055.84 in CASE 1 to $1303.57 in CASE 3 representing over $247 increase in customer incentive as a result of RES integration. The least incentive of about $5.5 per kWh was recorded in CASE 1 mainly because the transferred energy was less than 3% minimal. However, in CASE 3 over 112 kWh was transferred to the grid with a corresponding consumer incentive of over $36 per kWh.

This study has illustrated the viability of utilizing PSO methods for the effective resolution of the economic load dispatch problem with demand response and generator constraints. The study also portrayed the economic dispatch technique for generation, grid, and load that incorporates demand response to address the solar and wind curtailment issues resulting from the growing integration of large-scale power. The optimization of electricity distribution and the integration of grid design and demand response at the load side into the traditional economic dispatch model of power generation. This encourages the flexible generation of power and load within power systems to enable large-scale integration and consumption of solar and wind energy as shown in appendix A, B and C.

Future work on this demand side response should include additional optimization techniques and larger solar PV and wind energy powers to validate the efficacy of the technique in a complex microgrid. The number of customers that transfer power to the grid should also be increased to further optimize the demand side incentives.

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APPENDIX A

Solar PV=180.62 kW Wind Turbine =135.17 kW

G1 Kw	G2 Kw	G3 Kw	Pr Kw	x1 Kw	x2 Kw	x3 Kw	Pw Kw	Ps Kw
2.5200	2.6700	8.0100	1.2200	-0.3700	-0.5000	-8.9900	7.5600	0
1.8700	3.8300	8.4500	2.9000	-5.7000	0	-1.1500	7.5000	0
3.4300	5.9700	8.6500	3.0000	-1.5500	-0.0500	-0.2600	8.2500	0
3.0800	2.7700	8.0200	3.9400	-3.3000	-1.2600	-0.1500	8.4800	0
3.3800	4.5400	7.5500	1.0700	0	-6.0700	-0.0800	8.4800	0
3.1800	2.3700	4.8700	0.8200	0	-0.0400	-11.4000	9.4200	0
3.6200	4.5100	7.4900	2.4100	-2.6200	-1.2800	-1.2300	9.8200	0
1.4200	4.5100	7.6600	1.6000	-0.1600	0	-0.4000	10.3500	7.9900
2.3800	2.6200	8.1600	1.7000	-0.0500	-0.6700	-0.5000	10.8800	10.5600
1.0200	1.8800	8.3100	-0.6500	-1.7200	-0.8800	-0.5500	11.0100	13.6100
3.6100	4.4900	6.4300	-2.8700	-0.6000	-0.8600	-1.0000	10.9400	14.9700
2.6000	3.6800	8.8800	-2.1300	-0.8800	-0.5500	-1.0400	10.6800	15.4500
2.9900	2.8500	8.2600	-0.5500	-0.2200	-0.3600	-0.3500	10.4200	14.7800
1.9900	4.3100	8.3500	1.4300	-0.8700	0	-0.0100	10.1500	14.5900
2.5800	4.0400	8.6400	0.0800	-1.3900	-1.3500	-0.7900	9.6700	13.5600
3.6800	3.9100	8.8400	-2.3300	-0.0400	-6.7000	-0.0200	8.9800	11.8300
3.4600	4.2500	7.4300	0.2500	-0.2500	-2.6900	-3.8300	8.3700	10.1700
2.8700	3.8200	8.3300	1.5300	-0.5400	-1.4100	-6.3000	7.6100	7.6600
4.0000	5.3900	8.5900	3.7400	-8.1600	-1.3700	-0.6900	6.7000	0
3.5900	5.1600	9.0000	3.8000	-5.8100	-2.7800	-0.5400	5.7200	0
2.3000	4.3200	8.9300	2.7200	-1.0800	-5.7700	-1.7700	7.2100	0
3.4300	3.7500	7.5100	1.7800	-2.1500	-1.2200	-5.2000	7.7500	0
2.8300	5.8500	8.8000	1.5300	-0.6400	-3.1900	-1.7900	7.8800	0
3.8900	4.6900	9.0000	4.0000	-1.2400	-1.4300	-0.0600	7.6900	0

APPENDIX B

Solar PV=194.79 kW   Wind turbine=242.52 kW

G1 Kw	G2 Kw	G3 Kw	Pr Kw	x1 Kw	x2 Kw	x3 Kw	Pw Kw	Ps Kw
2.7700	2.9400	7.8400	2.7800	-3.7900	-3.3100	-0.8300	8.5700	0
3.8000	5.9600	8.6900	2.6600	-1.5800	-0.2600	-0.9500	8.9800	0
2.8400	4.7200	7.0300	2.3800	-2.3200	0	-3.6300	9.1200	0
2.6100	3.1400	5.2600	-0.0600	-1.0800	-0.8600	-9.6300	9.2400	0
4.0000	4.4700	6.6800	1.9600	-2.9600	-1.6500	-0.9800	9.5800	0
3.2900	3.4700	7.5800	0.9200	-1.8600	-4.5500	-1.0200	9.9700	0
1.9900	4.6900	6.5600	0.7400	-4.1200	-5.0400	0	10.4300	8.4200
3.0000	2.8000	5.5700	-2.3700	-6.3800	-0.2800	-0.0900	10.8600	9.6300
1.9300	2.7500	5.9100	-1.7900	-0.0800	-2.7100	-4.5000	11.0600	10.8800
3.4900	1.7800	8.2900	-0.6600	-0.6900	-0.1100	0	11.7800	14.8000
2.7600	1.4400	8.0600	0.0100	-1.7400	-0.0300	-0.0900	11.8700	15.6500
0.5000	1.9200	8.8700	-1.9100	-5.6900	-0.3100	-0.1100	11.9000	17.8900
1.5200	4.1200	6.0800	-0.1900	-0.1700	-0.7600	-2.0100	12.4000	17.9700
2.3200	3.3400	9.0000	0.0600	-0.4500	-0.0100	-1.7700	12.0800	16.5600
2.2100	1.2500	8.4500	0.2300	-0.1500	-0.4900	-6.1000	11.6000	16.4200
3.7500	3.5200	8.4000	2.8900	-0.3600	-0.1000	-1.8500	11.3200	15.2400
3.3100	5.3800	6.9600	1.9600	-3.3100	-0.1800	-1.0600	10.4100	14.1600
3.0700	5.5200	8.3700	-0.5600	-5.9500	-1.0400	-1.4100	9.6800	13.4500
3.6700	5.0400	7.6800	1.7600	-6.4500	-6.0300	-1.3100	9.2800	9.5400
3.8100	5.5800	8.5800	2.0800	-7.6900	-1.9400	-0.9900	9.0600	0
3.9500	6.0000	8.3400	3.4600	-3.0500	-1.3100	-0.7800	8.6400	0
3.8600	2.5700	8.9400	1.5700	-7.7400	-0.3700	0	8.4200	0
3.5000	3.7000	6.8900	2.6200	-0.3100	-7.5300	-0.0900	8.2200	0
3.4600	5.9200	8.1400	2.0500	-4.2800	-0.0900	-0.3700	8.0500	0

APPENDIX C

Solar PV=200.49 kW   Wind turbine=278.71 kW

G1 Kw	G2 Kw	G3 Kw	Pr Kw	x1 Kw	x2 Kw	x3 Kw	Pw Kw	Ps Kw
1.1600	3.5000	4.8000	2.3400	-5.7000	-5.7800	-0.9900	8.8000	0
4.0000	4.4600	6.7800	1.0700	-4.5100	-3.0500	-0.0300	9.2400	0
3.4500	4.5100	7.5800	1.1000	-3.9300	-0.0100	-2.3400	10.4500	0
1.4000	2.9300	8.8000	1.0500	-5.4400	-1.2100	-1.7000	11.5200	0
0.5800	2.6500	6.6100	-1.0700	-11.9400	-1.6900	-0.2800	11.6800	0
3.8600	4.8000	7.8500	2.1700	-0.2000	-3.6900	-0.1000	11.8000	0
1.7200	3.1700	7.7100	2.2200	-7.9700	-0.1400	-0.2200	12.1600	9.6700
2.0100	1.4200	7.5000	3.9900	-0.1000	-0.6200	-0.1200	12.7900	11.8900
2.1600	3.5400	6.4400	1.4100	-1.9900	-0.5000	-0.0500	12.4300	14.5800
2.0800	3.5500	5.4400	1.1400	0	-1.1500	-0.3400	13.6400	16.9800
0.7100	2.3500	7.0200	-0.0500	-2.9700	-1.0000	-0.1200	14.8300	17.8900
2.5100	1.5700	5.8900	-0.0400	-4.7900	-0.0400	-0.7300	14.5400	18.6500
1.4200	2.6400	5.6200	1.9400	-2.8300	-0.0100	-0.0100	13.9400	18.4200
1.7600	4.6300	6.0100	0.3700	-3.4800	-0.0500	-0.6600	13.4500	18.2100
3.9000	3.1600	7.7300	1.8400	0	-1.8100	-0.4300	12.8300	17.6500
3.9300	1.5800	8.3500	2.1100	-0.2900	-2.5700	-2.0400	12.9800	17.1100
3.5600	4.7600	8.6800	1.1000	-0.0100	-0.7000	-3.3500	11.5400	16.2400
2.8600	5.6600	8.4200	2.2700	-4.3400	-1.2200	-0.0200	10.6400	12.3400
3.4500	4.0900	7.2500	2.5900	-9.6200	-0.2700	-4.6600	11.8700	10.8600
3.0400	5.1400	9.0000	3.4300	-0.2400	-0.3900	-9.4300	9.9000	0
3.1300	1.9000	7.0200	1.1400	-7.3600	-3.4000	-2.9400	9.5300	0
3.3200	3.6000	6.6700	1.7500	-2.2800	-1.4500	-5.9900	9.4200	0
3.1000	2.5600	8.4300	-0.7200	-2.2500	-3.8200	-5.1900	9.6500	0
1.0400	5.7000	7.6500	2.5900	-2.3400	-0.2800	-4.7100	9.0800	0