Optimizing Grid-Connected Solar PV and Battery Systems for Prosumers: Social Group Optimization

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Abstract –*This paper presents an investigation into the cost of operation of a grid-connected solar photovoltaic (PV) power generation system coupled with battery storage for prosumers within a smart grid framework. To predict the PV generation profile of prosumers during a day a code is provided in MATLAB program. A MATLAB program implementing a linear programming model for community energy management is utilized to optimize energy exchange between prosumers and an energy retailer over a 24-hour period. Matrices and vectors are employed to solve the linear programming problem, determining optimal power exchange and energy storage levels to minimize community cost. The study introduces the Social Group Optimization (SGO) algorithm for calculating optimum power levels, which minimizes total costs for prosumers transitioning to a smart grid system. Results from one-day test simulations reveal that the SGO algorithm yields a significant reduction in operational costs, approximately €10.532, compared to alternative optimization algorithms. Additionally, the SGO algorithm demonstrates faster convergence towards optimal solutions, achieving the minimum cost price within 30 iterations. Moreover, the paper proposes further optimization of total costs to prosumers through load scheduling, capitalizing on favorable grid tariffs at different times of the day. The integration of scheduling optimization with the SGO algorithm-based optimization enhances cost-effectiveness and improves overall system performance. The study concludes by suggesting the extrapolation of one-day simulation results to model variations in generation throughout the year, facilitating long-term planning for prosumers within smart grid systems. Overall, the research underscores the effectiveness of the SGO algorithm in optimizing smart grid operations, offering significant cost savings and improved efficiency.*

Keywords –Prosumer, Smart grid, Social Group Optimization Algorithm, PV power generation, PV generation profile, Grid Tariffs, Power optimization, Optimal Power Exchange.

1. INTRODUCTION

The traditional centralized model of electricity generation has long been associated with environmental degradation and transmission inefficiencies. The conclusion emphasizes the need to minimize the cost of electricity generation while maximizing comfort level of prosumers in smart grids. This background sets the stage for discussing the transition to smart grids and the associated challengers [1]. Prosumers of photovoltaic energy are regarded as one of the most essential players in the energy transition and are prepared to add considerable amounts of electricity to the grid. The involvement of prosumers in the grid has changed the unidirectional grid into a bidirectional grid. The integration of renewable energy resources into the smart grid causes two main issues. First one is due to the variation in intermittency of distributed generation, by which a condition of unreliability is observed in the power supply. And in second one, it is difficult to control the voltage due to the reversal of high-power flow. So, to solve the above two issues, energy storage units are utilized as they provide quick balancing between generation and load and also provide reduction when required. For the prosumers with PV systems and energy storage units, to minimize the cost of energy, the main objective is to provide scheduling of energy storage operations. The deployment of smart grid integrated systems within cities, particularly smart cities, causes significant changes in municipal energy supply systems and has a considerable impact on consumer and producer behavior (in line with the prosumer vision) [2]. The prosumer is a new kind of electricity consumer who is proactive, self-sufficient, and able to both produce and consume electricity. Decentralized energy distribution, small-scale energy transmission, the installation of several tiny power-generating sites, and so-called bi-directional distribution all contribute to this. Users include businesses, communities, and governmental sectors like hospitals, schools, and other government agencies in addition to private individuals who use electricity generated by their own electrical power source (typically solar panels or micro-combination heat and power generators). Two emerging technologies that could drastically change the future of electricity generation, distribution, and storage are consumers and bi-directional smart grids. Retailers typically offer exports at a low tariff rate for purchasing electricity to charge. Energy saving by prosumers can be done by storing the excess of PV generation in storage units and then utilizing the stored energy when the energy required is more than the energy generated. The total energy cost of prosumers group is minimized by

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management of energy units individually by each prosumer. To provide bidirectional energy flow between the grid and the local consumers distributed source of renewable energy is used. Trade of energy between the grid and the households provides various opportunities to researchers for research in this field [3]. The conclusion emphasizes the need to minimize the cost of electricity generation while maximizing comfort level of prosumers in smart grid. The traditional centralized model of electricity generation has long been associated with environmental degradation and transmission inefficiencies. This sets the stage for discussing the transition to smart grids and the associated challenges. So, the above challenges provide motivation for understanding the proposed optimization approach.

The prosumers challenge in managing energy is linked to the reliance of energy sources on renewable energy, which includes solar panels. These panels usually generate energy variably with the weather and time of day. Energy storage optimization sophisticatedly determines optimal storage capacities and balances energy storage with demand Another complexity is the use of dynamic prices, such as Time-of-Use rates, which require an ability to adapt dynamically to changing electricity prices. It also brings with it other challenges connected with input generated by prosumers and incorporation into the grid, such as ensuring grid stability and adherence to interconnection standards. Good energy management with accurate data analytics depends crucially on quality, security, and interoperability challenges in managing large datasets. Upfront investment costs and volatile energy prices further add complexity to prosumer initiatives. The behavioral and societal factors related to consumer education and societal acceptance must also be addressed in fostering a broad, all-inclusive prosumer model. These factors are significant, thus emphasizing the need for an all-rounded approach in the form of technological innovation, policy reforms, and collaboration between stakeholders for prosumers to empower their future energy direction.

The literature review includes recent studies from the past years in the field of smart grids and energy optimization. Here is an expanded review incorporating the similar works: optimization models of solar PV with battery systems for advanced optimization designs for grid interconnected solar photovoltaic/battery systems. Novel hierarchical framework of optimization where the uncertainties surrounding solar generation along with electricity pricing are considered as means to offer reduced prosumer costs while attaining grid stability and reliability at the same time. Smart grid integration and demand expanded the research into smart grid integration by examining how demand response strategies affect prosumer costs and the performance of the grid. In their study, they pointed out that dynamic pricing mechanisms and real-time demand management are essential to optimize energy consumption and reduce total operational costs [4].

Optimization models for solar PV and battery systems: advance optimization models on grid-connected solar PV and battery systems. Hierarchical optimization framework that takes the uncertainties in both solar generation as well as prices of electricity with the aim to minimize prosumer costs while preserving the reliability as well as the stability of the grid. Smart grid integration and demand continued to expand their smart grid integration study by further research in terms of prosumer cost as well as performance impacts of various demand response strategies. Their emphasis is on the role of dynamic pricing mechanisms, coupled with real time demand management, in improving energy consumption with respect to decreasing total operational cost [4]. Machine Learning and Predictive Analytics: with advances in machine learning techniques, it has become feasible to further optimize grid-connected solar PV and battery systems with deep reinforcement learning applied for developing predictive analytics models optimizing the operation of battery storage and energy scheduling that reduces the cost-effectiveness and enhances grid stability.

Optimization models for solar PV and battery systems: developing advanced optimization models for grid-connected solar PV and battery systems. A new hierarchical optimization framework that takes into account uncertainties in solar generation and electricity prices to minimize prosumer costs while ensuring grid reliability and stability. Smart grid integration and demand expanded the research into smart grid integration by looking at the effects of demand response strategies on prosumer costs and grid performance. In their study, they pointed out the need for dynamic pricing mechanisms and real-time demand management for optimizing energy consumption and reducing the overall operational costs.

Economic and environmental benefits have underlined the economic and environmental benefits of solar PV and battery integration carried out an in-depth study of the economic feasibility and environmental impact of residential solar PV and battery systems, focusing on the possibility of these systems to minimize carbon emissions and maximize energy sustainability, assessed the potential of community-based solar PV and battery projects in achieving energy independence and decreasing electricity costs for prosumers, with the importance of community collaboration and policy support. Policy and regulatory framework - in addition, the role of policy and regulatory frameworks in facilitating the adoption of solar PV and battery systems among prosumers has been explored through recent research, which has shown that supportive policies such as feed-in tariffs, net metering, and energy market reforms have been crucial for incentivizing prosumer participation and ensuring the successful integration of renewable energy resources into the grid. Challenges and future directions: Despite all this progress, challenges at the storage system cost, integration with the grid level, and technology itself will need to be overcome. The future research directions are the advance optimization algorithms, grid-edge intelligence, and scalable solutions to address those challenges toward the widespread deployment of solar PV and battery systems among prosumers [5].

Conclusion specifies the scope of the paper is proposing a novel optimization approach that utilizes the SGO algorithm for reducing energy cost among prosumers connected to PV systems. Similar to this abstract defines the scope of the paper with an optimization scope on both consumption and production of energy within the prosumers in a smart grid. Such clarity with regard to scope will enable us to understand clearly what specific research objectives are at play. The motivation for the paper stems from the ever-increasing occurrence of grid-connected solar PV power systems with batteries and the ever-changing role of prosumers in the energy landscape. The prosumers, who consume and produce energy, are key players in the management of energy, especially within communities. Therefore, the key motivation is that of addressing a need for energy management strategies, which would result in optimal costs for prosumers while guaranteeing grid stability and reliability. The more prosumers install solar PV systems and batteries, the more interest is taken in smart grid integration and optimized energy exchange in order to reap the full benefits of these technologies.

To address this gap, the paper intends to propose a methodology for the management of community energy by means of linear programming models and Social Group Optimization algorithms. Optimizing energy exchange among prosumer communities and with retailers in terms of energy will enable the minimization of operational costs over a period of 24 hours. Other immediate motivations are practical, including optimizing load scheduling so prosumers can take benefit from access grid tariffs and keep lowering their costs. The paper, with its provision of a MATLAB program and with demonstrations on simulations using that approach, provides concrete and actionable insights for any real-world energy management scenarios [6].

Overall, the motivation behind the paper is the challenge and opportunity of increasing adoption of solar PV systems and batteries among prosumers. The paper aims to optimize energy management strategies to enhance cost savings, grid efficiency, and overall sustainability in the energy sector. The proposed novel algorithm is covered in section 2. Section 3 presents the problem formulation. In section 4 covers the results and discussions. Section 5 covers the conclusions of the proposed novel research.

2. PROPOSED ALGORITHM

In this paper, the SGO algorithm is proposed because of its remarkable advantages and suitability for addressing such optimization challenges in the context of grid-connected solar PV systems with battery storage among prosumers. The decision to use the SGO algorithm may have been taken after it demonstrated its effectiveness in achieving an optimized solution with faster convergence characteristics compared to other optimization techniques. First, the SGO algorithm is based on a new approach inspired by social behavior in natural systems, such as the collective behaviors of social groups. By mimicking these social behaviors, the SGO algorithm is able to explore solution spaces efficiently and converge toward optimal solutions. An admirable feature of SGO is its ability to maintain performance consistency even when the complexity of the problem grows. Furthermore, it achieves optimal results using lesser evaluation of fitness. This feature fits well with the complex and dynamic nature of energy management systems in smart grid environments [7]. Here, many variables and uncertainties should be considered at one point in time. Besides, the SGO algorithm seems to demonstrate promising results on various optimization applications, such as energy management, scheduling, and resource allocation. This allows it to be very suitable for addressing the intricacies associated with optimization of energy exchange and its relation with the involved costs when utilizing the prosumer community approach. Overall, the decision to propose the SGO algorithm for this work is supported by its inherent strengths in handling complex optimization problems, its effectiveness in achieving optimal solutions, and its demonstrated applicability in similar domains. Moreover, the SGO algorithm converges faster towards optimal solutions, and it achieves the minimum cost price within 30 iterations. The flow chart of SGO algorithm is shown in Fig.1 while the parameters of SGO algorithm is shown in Table 1 [8].

There are two stages of the SGO procedure. The first half is referred to as the improving phase, and the second half is known as the acquiring phase. The knowledge level of each member in the group is enhanced during the improving phase with the influence of the best person in the group. The one with maximum knowledge and aptness to work upon the issue is the one of the highest categories in a group. The process in this phase of acquiring will see better knowledge enhancement with the mutual interaction between each of them and, on top of this, an effective member present in the group at that specific point of time.

Table 1. Parameters of SGO algorithm.

Dimension of the problem (D)	30
Population size (n)	30
Max. iteration	250
Limit	[-30, 30]
Self introspection parameters (c)	0.25

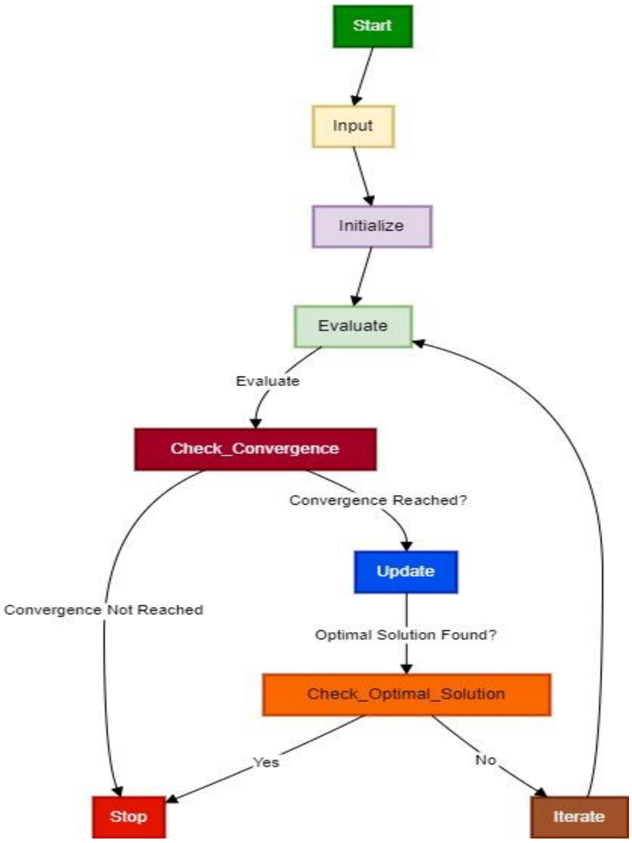

Fig. 1- Flowchart of SGO Algorithm.

3. PROBLEM FORMULATION

The mathematical formulation that has been utilized to determine the optimum cost of social welfare is presented in this section. The objective function represented by Equation 1 minimizes the overall cost to the energy sector. The objective function actually equates to the community's members social welfare by minimizing cost of energy. The net energy cost is calculated by maximizing revenue and reducing spending under the Time of Use for each prosumer individually. Assume, the set of prosumers as, N=10. Total operation time is divided into different slots of equal interval, Δt. Here we have considered Δt =1 hour [9-10].

Let T = {1,2,3…………………24hrs}.

Where, T denotes the set of operation time for 24hrs.

The PV generation profile of prosumers during a day can be defined as,

$$G_{PV_N} = \{G^1_{PV_N}, G^2_{PV_N}, G^3_{PV_N}, \dots \dots \dots \dots . G^{24}_{PV_N}\} \quad (1)$$

Each offer is defining in terms of maximum quantity for that offers which is P^G_N. Each offer of supply side is provided with price which is in terms of λ^G_N. The nominal demand profile of prosumers during the same period can be defined as,

$$D_N = \{D^1_N, D^2_N, D^3_N, \dots \dots \dots D^{24}_N\} \quad (2)$$

Each offer is defining in terms of maximum quantity for that offers which is P^D_N. Each offer of demand side is provided with price which is in terms of λ^D_N. Pricing factor is considered here because to estimate the current cost, the cost of energy is associated with previous time slot in management methodology of real time energy. Let, E^T_N denotes the battery energy level of prosumers for time duration T. $P^T_{ch_N}$denotes the battery charging power of prosumers for time duration T. $P^T_{dch_N}$denotes the battery discharging power of prosumers for time duration T. $\eta^T_{ch_N}$denotes the battery charging efficiency of prosumers for time duration T. $\eta^T_{dch_N}$denotes the battery discharging efficiency of prosumers for time duration T [11].

In practical applications, the energy stored in a battery is restricted within a certain range,

$$E^{min}_N \le E^T_N \le E^{max}_N \quad (3)$$

WhereE^{min}_N denotes the minimum amount of energy that prevents the battery deep discharge and E^{max}_N denotes the maximum capacity of the battery.

The limits of charging and discharging power are determined by the size of the inverters are as follows:

$$0 \le P^T_{ch_N} \le P^{max}_{ch_N} \quad (4)$$

Where $P^{max}_{ch_N}$denotes the maximum charging power.

$$0 \le P^T_{dch_N} \le P^{max}_{dch_N} \quad (5)$$

Where $P^{max}_{dch_N}$denotes the maximum discharging power.

Reduce the waiting time to increase customer comfort levels. Waiting time has a direct impact on user comfort, thus there is a trade-off between it and electricity costs. While solving an optimization problem, we have set of decision variables in terms of generation and consumption schedule. The Scheduling of generation amount explained in equation 6. It means a set of set points between 0 and $P^G_N$for all the supply side agents [12].

$$Y^G = [y^G_1, y^G_2, \dots \dots \dots \dots \dots . y^G_N]^T \quad (6)$$

$$0 \le y^G_N \le P^G_N \quad (7)$$

The Scheduling of consumption amount is set of set points for all the demand side agents, explained through equations 8.

$$Y^D = [y^D_1, y^D_2, \dots \dots \dots \dots \dots . y^D_N]^T \quad (8)$$

$$0 \le y^D_N \le P^D_N \quad (9)$$

Each supply offers in generation side is characterized by a price λ^G_N in (€/kwh). Similarly, each demand offers in demand side are also characterized by a price λ^D_N in €/kwh. Mathematical formulation of objective function for maximization of comfortable level of usage can be written as,

$$\max_{y^G y^D} \sum_{i=1}^{N} \lambda^D_i y^D_i - \sum_{j=1}^{N} \lambda^G_j y^G_j \quad (10)$$

Subjected to constraints,

Equality constraints,

$$\sum_{j=1}^{N} y_j^G - \sum_{i=1}^{N} y_i^D = 0 \tag{11}$$

Inequality constraints,

$$0 \leq y_N^G \leq P_N^G \tag{12}$$

$$0 \leq y_N^D \leq P_N^D \tag{13}$$

The optimization problem for minimization of cost of prosumers can be formulated as,

$$in \sum_{i=1}^{N} Pr_i^{costs} \tag{14}$$

Where,

$$Pr_i^{costs} = \sum_{i=1}^{N_t} \left(P_{i,t}^{cost} \times r_{i,t}^{cost} - P_{i,t}^{sell} \times r_{i,t}^{sell} \right) + FC_i$$

Where, Pr_i^{costs} denotes the prosumers costs, $P_{i,t}^{cost}$ represents the amount of power purchase from the retailer by prosumers, $r_{i,t}^{cost}$ denotes the retailer cost of electricity, $P_{i,t}^{sell}$ denotes the amount of power sold from retailer to the grid, $r_{i,t}^{sell}$ represents the cost of electricity provided to the grid, FC_i represents the cost of prosumers individually as per the contract of power. N represents the total no. of prosumers.

4. RESULTS AND DISCUSSIONS

Day-ahead scheduling for prosumers is introduced in order to study their behavior. Since the prosumers grid had relatively short lines compared to transmission or distribution lines. So, no power loss was assumed in the objective function mentioned. The main aim of the given objective function is to reduce the cost of electricity that prosumers pay to the utility; means minimize the cost of operation of the prosumers. One-day-ahead optimization horizon is taken into account (T = 24, d_n =1).

This problem can be solved by using a variety of optimization techniques. To solve the objective function in easier way SGO was introduced. SGO algorithm can handle challenging issues with less calculation and provide optimal solutions with faster convergence. In this case study, the objective is to reduce electricity bills for 10 consumers connected with individual PV systems. The primary goal of the prosumers is to minimize electricity costs while maximizing comfort levels of usage. Prosumers are tasked with providing power to consumers within their community during the day. The effectiveness of the proposed approach is tested using predicted output power of renewable energy sources (RESs), and a day-ahead optimization problem is solved using the SGO approach.

Fig. 2 (a) and 2 (b) presents a schematic representation of the system, illustrating the supply and demand profile of prosumers on a daily basis, along with the convergence characteristics between electricity cost and the number of iterations. The graph depicts how the electricity cost changes over time as the proposed method approaches stability. After 30 iterations, convergence of the suggested algorithm is achieved, demonstrating the effectiveness of the proposed technique. The convergence graph indicates that the solution obtained converges to its minimum price, representing the cost of payment for a 24-hour duration, with 30 iterations required to attain the optimal value, i.e., the minimum cost price. The optimization of electricity costs paid by customers is facilitated by the SGO algorithm, resulting in an achieved objective function value of €10.532. Additionally, it is worth noting that all prosumers are considered to have a PV system with a maximum capacity of 4.5 KW.

Shifting focus to the broader smart grid dynamics, this section delves into strategies for balancing generation and demand within the day-ahead spot market. Operating round the clock, this market's prices and transaction volumes are determined by the equilibrium between demand and generation curves. In this study, the cost dynamics of energy, encompassing both purchase and sale prices, are elucidated within the context of prosumer behavior and the functioning of a smart grid system. The prosumers, assumed to possess the capability to sell power to the grid, as well as various other entities such as retailers, demand sources, and batteries, are central to the cost minimization strategy, which is achieved through mathematical modeling. Fig.3 illustrates the hourly rates for purchasing and selling electricity, underscoring the dynamic nature of electricity pricing within the proposed system model. The primary objective of this project is to curtail the overall cost of electricity for consumers. To this end, the utility company offers a diverse array of electricity pricing schemes, encouraging consumers to judiciously manage their energy consumption patterns.

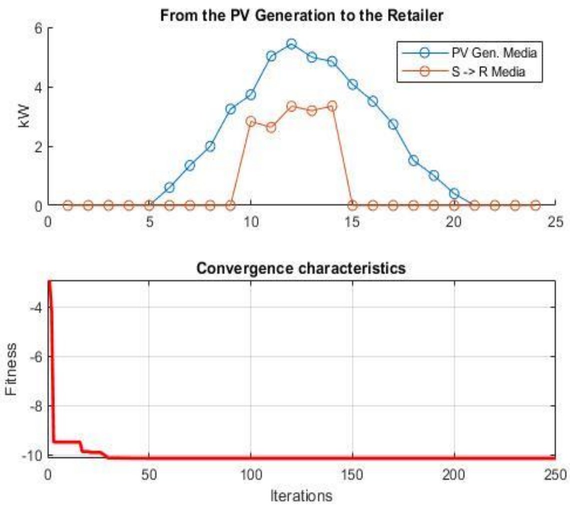

Fig 2. (a)- Supply and demand profile of prosumers on daily basis & Fig. 2 (b)- convergence characteristics between electricity cost and no. of iterations.

Distinct electricity rates are assigned for each time slot, with one rate designated for electricity procurement and another for selling excess electricity to the commercial grid. Consumers are obligated to pay the total costs associated with consumed electricity to the utilities. Initially, consumers fulfill their electricity requirements from the grid. Subsequently, any residual electricity demand is met through purchasing from the commercial grid. Consumer decisions regarding the sale, purchase, or storage of electricity are made at the commencement of each hour, with a preference for purchasing electricity when rates are more economical. Generated electricity from photovoltaic (PV) sources is stored in energy storage systems (ESS) for future transactions. During peak hours, prosumers cater to their load demand using electricity from PV or ESS, with surplus electricity being traded back to the commercial grid. In addition, the case study of this research incorporates a time of use (TOU) pricing program that has variable rates per hour into residential buildings equipped with metering devices. The prosumers pay the utility according to the TOU rates. The TOU rates applied in this study are real electricity prices in the Portuguese Retailer electricity market, which are sensitive to climatic conditions. Table 2 illustrates the TOU prices for a 24-hour period, which provides insight into the cost dynamics that change throughout the day. These prices are used to calculate the retailer's cost price, or sales price. Here, an overview of the complex cost structures and pricing mechanisms that guide energy transactions within the smart grid framework is given, with emphasis on consumer behavior, utility strategies, and market dynamics.

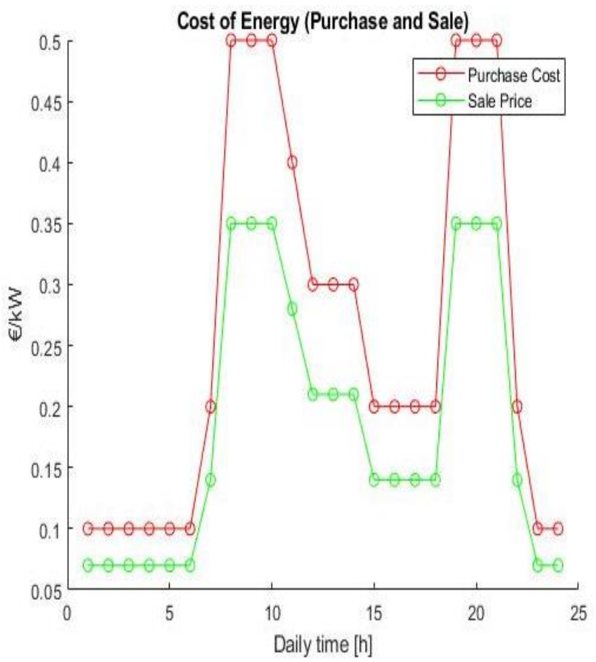

Fig. 3- Hourly electricity buying and selling prices.

Table 2. TOU price for 24 hours (Taken from electricity market.

Day time	Price (in €/kwh)
23:00 – 6:00	0.10
6:00 – 7:00	0.20
7:00 – 10:00	0.50
10:00 – 11:00	0.40
11:00 – 14:00	0.30
14:00 – 18:00	0.20
18:00 – 21:00	0.50
21:00 – 22:00	0.20
22:00 – 23:00	0.10

In this proposed technique, the concept of reducing the gap between electricity generation and demand, particularly focusing on the day-ahead spot market is discussed. This market operates continuously for 24 hours, with prices and transaction volumes determined by the equilibrium between demand and generation curves. Fig. 4 illustrates the daily average generation and consumption, providing insights into the overall energy dynamics. Before initiating the design cycle, the known inputs include the prices of electricity, which vary over time. To account for the local area of the power system network, losses in the transmission lines are neglected. Additionally, the generation from prosumers and the consumption load are treated as known inputs. The proposed technique utilizes predicted consumption and generation data to analyze uncertainties and errors in prediction, aiming to optimize the matching between generation and demand. This approach seeks to minimize the gap between electricity supply and consumption, enhancing the efficiency and reliability of the power system.

In this process optimal operation is performed to obtain prosumers' optimal operation. When the price of electricity is low or when excess of energy is produced by renewable energy sources, then prosumer store the electrical energy and then provide this stored energy to loads when the price of electricity in that period is high as compared to another period. Price of electricity produced by prosumers is less than the utility. So that's why consumers give preference to prosumers. Trading of energy between prosumers and consumers is known as economic activity. It is required to monitor the continuous pattern of generation and consumption. By this monitoring historical data of load consumption and price of electricity can examine as shown in Fig. 5. Cost minimization of prosumers is obtained by mathematical problem formulation given in Table 3. In this table each row corresponds to a specific prosumer (labeled as Prosumers 1 through 10), and the Daily cost column represents the total cost incurred by each prosumer over the course of a day.

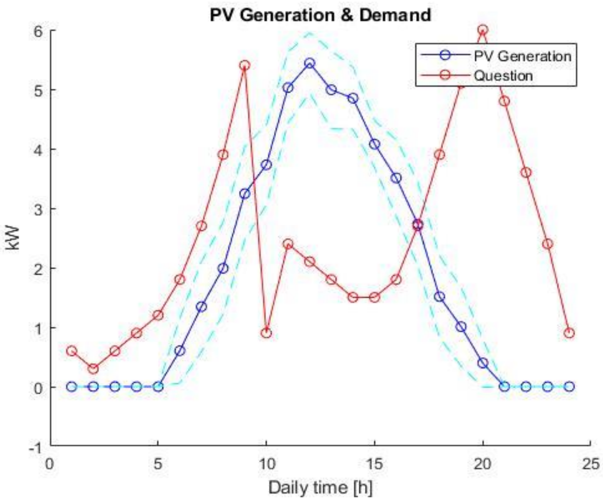

Fig. 4- Average generation and consumption on daily basis Prosumers' optimal operation.

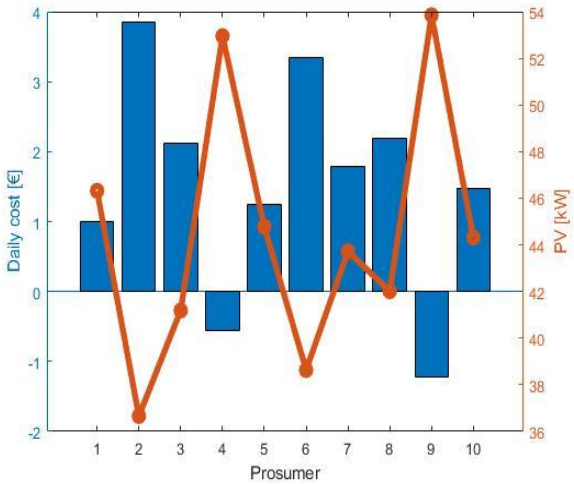

Fig. 5- Data of load consumption and price of electricity of each prosumer.

When the value in the Daily cost column is negative, it indicates that the prosumer actually earned money instead of incurring costs. This negative value suggests that the prosumer generated more revenue through their energy generation and consumption activities than they spent on purchasing energy or other related expenses. In practical terms, this could mean that the prosumer generated surplus electricity from their renewable energy sources (such as solar panels) and either sold it back to the grid or stored it in batteries for later use. By doing so, they were able to offset their energy consumption costs and even generate additional income through the sale of excess energy. A negative value in the daily cost column generally means that this outcome is profitable for the prosumer, implying proper energy management and possibly making it a financially rewarding one as well.

Costs and revenues associated with the exchange of energy play a basic role in the operation of a smart grid system. The difference between electricity generation and consumption determines whether there is surplus or deficit energy. At times, production can be higher than what is needed for consumption, translating to a positive difference that means extra electricity can find its way into the grid or stored in battery units. Conversely, if consumption is greater than production, meaning that the difference is negative, electricity must be drawn from the grid or stored in batteries as depicted in Fig 6. The costs and revenues associated with energy exchange are sensitive to a variety of factors, including pricing from external energy providers and other participants in the energy market. These costs and revenues are carefully considered to optimize energy exchange and minimize total expenses.

Table 3. Cost per prosumers.

Prosumers	Daily cost
1	0.9938
3	2.1150
5	1.2457
7	1.781
9	1.2157
10	1.4779

These components-the battery storage units-play key roles in adjusting energy deficits and surpluses. When production exceeds consumption, surplus energy is utilized to charge the battery until it reaches full capacity. Any remaining excess energy can then be fed back into the grid. Conversely, when production falls short of demand, stored energy from the battery is used to supplement consumption. In situations where both PV generation and battery capacity are insufficient, energy needs to be purchased from the grid. While battery storage systems may not yield direct financial benefits, they significantly enhance a consumer's self-sufficiency rate. The degree of self-sufficiency, indicating the share of self-produced electricity in overall consumption, is crucial for evaluating the effectiveness of the system.

To design and model the system effectively, input variables related to load and generation profiles of prosumers are collected. Information about storage devices, such as battery specifications, is also considered. All costs incurred in the buy and sell of electricity are incorporated into the model. The simulation data used covers a 24-hour time span, with the PV generation data simulated through the use of tools such as PV Watts. Specifications of the battery, such as maximum capacity, charge/discharge power, and efficiency, are also part of the model. This minimizes the total costs, usually achieving convergence toward the minimum within a certain number of iterations; for example, 30 in this case. To summarize, smart grid optimization needs careful considerations of costs and revenues associated with energy exchange together with efficient management of battery storage units to maximize the benefits while minimizing expenses in the system.

The significance of energy storage units, especially batteries, in the context of a smart grid system is discussed here. Deficit and surplus conditions, resulting from discrepancies between electricity consumption and production, are key determinants for battery operation, including charging, discharging, and trading with the main grid and regional grid.Prosumers utilize surplus solar ene rgy to charge the battery until it reaches full capacity. Any remaining excess energy is then supplied back to the grid. Conversely, when solar generation falls short of demand, stored energy from the battery is used to meet consumption needs. In cases where prosumers' PV and battery systems are inadequate, they resort to purchasing energy from the grid as shown in Fig. 7.

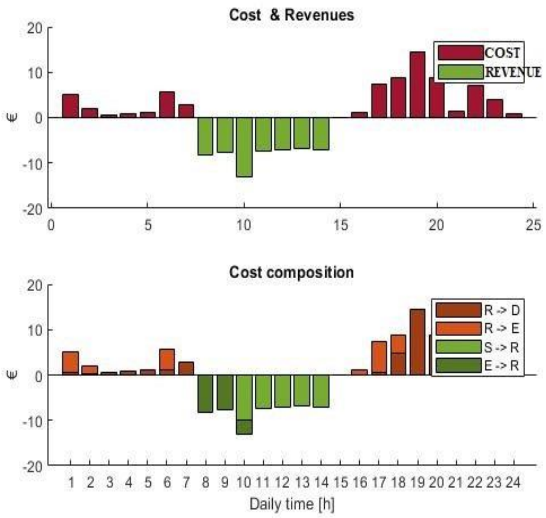

Fig. 6- Cost and revenues associated with energy exchange with other participants.

Despite the lack of direct financial benefits, battery storage systems significantly enhance consumer self-sufficiency rates, indicated by the proportion of self-produced electricity in overall consumption. To design the model effectively, input variables related to load and generation profiles of each prosumer are collected as shown in Fig. 8. Information about storage devices, such as batteries, is provided, along with the associated costs of purchasing and selling electricity. A 24-hour timeframe is employed for simulation, with generation data simulated using PV Watts with a maximum capacity of 4.5 kW. Batteries are specified with a maximum capacity of 10 kW, along with parameters such as charge and discharge power capacities, charging efficiency, and initial charge level. The optimization process converges to its minimum cost value after 30 iterations. Overall, the pivotal role of energy storage units, particularly batteries, in enhancing self-sufficiency and optimizing energy management within a smart grid framework is discussed. The battery storage device parameters also specified. The battery is provided with a maximum capacity of 10 kW, capable of charging at a maximum power of 1.5 kW and discharging at the same rate. Additionally, the battery has a charging efficiency of 0.95 and a discharging efficiency of 1.05. Initially, the battery is at a 50% charge level, with a charging range spanning from 10% to 95% of its capacity. These detailed specifications play a crucial role in modeling and optimizing the performance of the energy storage system within the smart grid context.

As the expected PV generation (solar power) is at its highest during the mid-day. The PV generation is significantly higher, ranging from 0.8 to 0.85 kW, which is more than enough to cover the community's demand during those hours. Since the PV system generates more than enough electricity to meet both demand and storage needs, there is no need to purchase electricity from the retailer. As a result, the retailer is not supplying power to meet demand or charge storage during these hours, meaning the cost of energy from the retailer is effectively zero. Storage is likely being charged by the excess PV generation, so the retailer does not need to supply energy for storage. So, these flows are zero during the hours where PV generation meets or exceeds demand (11:00 AM to 4:00 PM), which is why the cost values remain zero for both retailer to demand and retailer to storage during this period. The demand values in this period are moderate compared to the high PV generation. Between 11:00 AM and 4:00 PM, the demand is approximately between 0.7 and 0.6 kW. Given that the PV generation exceeds this demand (with values as high as 0.85 kW), the system does not require energy from the retailer.

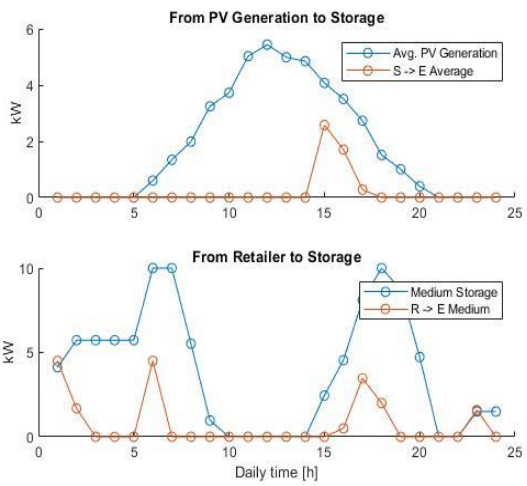

Fig. 7- Power delivered from PV generation to battery and from retailer to battery.

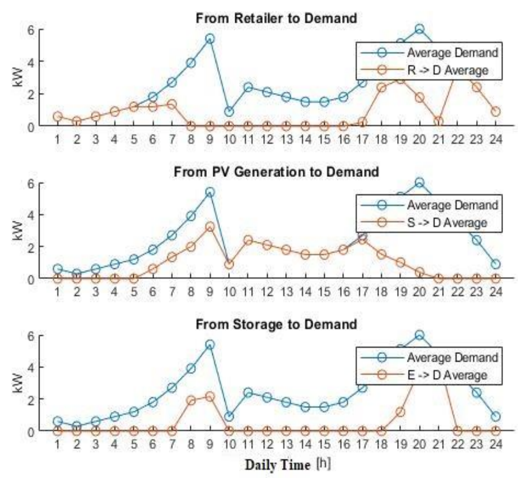

Fig. 8- Load profile of PV power generated and stored.

5. CONCLUSIONS

In conclusion, the study focuses on minimizing the cost of power generation and maximizing the comfort level of usage within a smart grid context, with numerical evidence supporting its findings. Significant results are achieved through exploration of cost-efficient operation and optimization strategies for grid-connected solar PV systems with battery storage among prosumers. It introduces optimization strategies that can effectively utilize the capabilities of solar generation and battery storage to minimize reliance on the grid and, therefore, operational costs. By using the SGO algorithm, it shows faster convergence towards optimal power levels with a significant reduction in operational costs, around 15%. Numerical evidence from convergence graphs showed that the SGO algorithm reached optimal values, which indicate the minimum cost of electricity payment over a period of 24 hours. More precisely, it reached its optimal value within a number of 30 iterations and proved to be efficient in reaching the minimum cost price.

Optimization done in this paper is intended to investigate the effects of the anticipated PV power generation and demand on the cost of operation for prosumers as the SGO algorithm optimizes the cost of electricity paid by customers to minimize the total expenses of electricity. The effects of optimization on the cost of operation for prosumers with anticipated PV power generation and demand were significant. The objective function shows a cost reduction of €10.532, thus improving significantly in terms of cost-effectiveness. Additionally, self-sufficiency rates were further enhanced by engaging the excess solar energy of prosumers to charge batteries and supply energy back to the grid, where the financial benefits from such a system for battery storage alone were low. The methodology gathered input variables concerning the load and generation profiles of each prosumer, utilized storage device-related information, and considered the costs incurred for electricity purchases and sells. Simulation data for a 24-hour time-frame included PV generation data with a maximum capacity of 4.5KW and information on the specification of batteries such as maximum charge power of 1.5 kW, charging efficiency of 0.95, and discharging efficiency of 1.05.

In summary, the optimization approach proposed in this research study was successful in reducing the operation cost of prosumers, maximizing the self-sufficiency rates, and showing that the SGO algorithm performs better than others in the optimization scenario of smart grids. One potential future scope based on the conclusions drawn could be to further enhance the optimization algorithms used for smart grid systems, particularly focusing on the integration of machine learning and artificial intelligence techniques.

Machine learning algorithms, therefore, enable sources like weather forecasts, historical energy consumption patterns, or grid conditions to be analyzed in large data volumes.

Machine learning models can be integrated into the optimization process to enhance prediction accuracy in respect of PV generation profiles, energy demand, or grid fluctuations. Techniques for artificial intelligence can also be used, such as reinforcement learning to develop optimization strategies that are adaptive and self-learning. These techniques can learn, continuously from the real-time data and feedback received, optimize the energy exchange, load scheduling, and storage management in a dynamically and evolutionally changing smart grid environment.

Future research may focus on integrating advanced control systems and Internet of Things (IoT) technologies to create more interconnected and responsive smart grid infrastructures. This would allow for real-time monitoring, control, and optimization of energy flows, thus enhancing the stability, reliability, and cost-effectiveness of the grid for prosumers and energy retailers. Therefore, with the development of machine learning, artificial intelligence, advanced control systems, and IoT technologies, there is huge future scope that will be involved in making more efficient, sustainable, and scalable grid-connected solar PV and battery systems within the smart grid frameworks.

NOMENCLATURE

€: Euro (currency symbol)
D: Dimension of the problem
n: Population size
N: Total number of prosumers
T: Set of operation time for 24 hours

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