



Optimal Management of Energy Storage Systems for Peak Shaving in a Smart Grid

Firas M. Makahleh¹, Ayman Amer², Ahmad A. Manasrah¹, Hani Attar², Ahmed A. A. Solyman³,
Mehrdad Ahmadi Kamarposhti^{4,*} and Phatiphat Thounthong⁵

¹Department of Mechanical Engineering, Al-Zaytoonah University of Jordan, Amman, 11733, Jordan

²Department of Energy Engineering, Zarqa University, Zarqa, 13133, Jordan

³Department of Electrical and Electronics Engineering, Faculty of Engineering and Architectures, Nisantasi University, Istanbul, 34398, Turkey

⁴Department of Electrical Engineering, Jouybar Branch, Islamic Azad University, Jouybar, Iran

⁵Renewable Energy Research Centre (RERC), Department of Teacher Training in Electrical Engineering, Faculty of Technical Education, King Mongkut's University of Technology North Bangkok, 1518, Pracharat 1 Road, Bangsue, Bangkok, 10800, Thailand

*Corresponding Author: Mehرداد Ahmadi Kamarposhti. Email: mehrdad.ahmadi.k@gmail.com

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Abstract: In this paper, the installation of energy storage systems (EES) and their role in grid peak load shaving in two echelons, their distribution and generation are investigated. First, the optimal placement and capacity of the energy storage is taken into consideration, then, the charge-discharge strategy for this equipment is determined. Here, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used to calculate the minimum and maximum load in the network with the presence of energy storage systems. The energy storage systems were utilized in a distribution system with the aid of a peak load shaving approach. Ultimately, the battery charge-discharge is managed at any time during the day, considering the load consumption at each hour. The results depict that the load curve reached a constant state by managing charge-discharge with no significant changes. This shows the significance of such matters in terms of economy and technicality.

Keywords: Cost; energy storage; particle swarm optimization (PSO); peak load; smart grid

1 Introduction

The Use of a smart grid improves the accessibility to electricity, especially during peak load hours. In other words, using such a grid helps control the amount of load inflicted on the grid and reduces the possibility of power outage in different parts of the grid by preventing customers' electricity over-use during peak hours. In addition, the quality of supplied electricity to the customers improves [1–5]. The electricity price is higher during peak load hours compared to other times of the day. If we present the electricity prices to the consumers, they will be able to manage their electricity consumption. In



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other words, they can shift non-necessary expenditures to off-peak hours and reduce their electricity consumption during peak load hours where electricity price is high. By providing an infrastructure connecting the electric companies and consumers, the smart grid enables the electric companies to present information associated with electricity prices to the consumers. Despite the current highly equipped and advanced power grid, it is not complete and some of its approaches need fundamental changes [6,7].

With the help of information and communication infrastructure, the smart grid can help us achieve our goals. While generating required electricity during peak load hours is one of the most important concerns of electric companies, peak load management is one of the major problems in power generation and distribution. Numerous objectives have been presented and investigated for smart grids; just like any other state-of-the-art technology [8–12]. One of the crucial objectives of the smart grid is peak load shaving. There are many methods that can be utilized in power grids for peak load shaving. The energy storage system (ESS) is one of these methods and is one of the required infrastructures to create and develop electricity smart grids [13,14]. The research investigates the optimal installation and placement of the storage in the smart grid and will show that installing the storage will help reduce the level of electricity consumption during peak load hours. By taking into consideration the increasing electricity generation cost, electricity should be put to use immediately after being generated. Electricity storage is a costly process, which has to be done with the economic imposition of electricity trading [15–19].

Numerous studies have been conducted in recent years in the field of energy storage systems by the introduction of smart grids and unsteady electric prices during different times of the day and the use of distributed generation resources. In this section, previous literature regarding this field is reviewed. In [20], suitable storage is determined for a wind farm. In this paper, an economic dispatch has been utilized for this objective. The objective of these studies is to maximize the profit achieved by installing distributed generation and storage for the resource owners and using them in power systems to reduce electricity costs. Results depict that using energy storage systems can help reduce the annual cost of electricity. Moreover, using energy storage systems alongside renewable energies (such as wind) can help improve the inclusion of these types of resources inside the power systems. In [21], the economic analysis method is utilized in order to find suitable storage. This method is inspired by the net present value (NPV) profit. The genetic algorithm is utilized in order to find the maximum profit achieved by NPV. A micro-grid is utilized in the study that consists of a number of distributed generation resources, e.g., solar cells, fuel cells, and micro-turbine. One of the main reasons for using storage is unsteady electricity prices during the day. In [22], temporal planning is proposed for storage by taking the time of use (TOU) condition into consideration. In this paper, particle swarm optimization is utilized. In this method, storage is considered alongside the wind farm and the impact of unpredictable wind speed is taken into consideration. Simulations are conducted on an industrial load.

The extensive use of energy storage systems is one of the objectives of electricity smart grids. In [23], the optimal performance of these systems is investigated in smart grids. In [23], the study network consists of a system with 17 buses, a solar power plant and the wind farm. The genetic algorithm is utilized to find the optimal location and capacity of capacitor and storage. Next, economic dispatch is utilized for determining the optimal performance of the storage, grid, and distributed generation resources. In [24], an optimal strategy is proposed to manage the storage for improving the performance of the wind farm. In this paper, a dynamic programming model is utilized. According to this model, the generated power by the wind farm should be able to follow the load curve. The optimization objective is to maximize the profit by the energy sale. Reference [25] determines an optimal capacity and strategy of energy storage performance for peak load shaving. Firstly, storage

capacity is determined in order to reduce energy purchases from the grid. Next, storage performance strategy is determined aiming at reducing payable expenses. In this paper, simulations are conducted on an industrial load. In [26], the optimal capacity and location of the storage and the capacitor are determined with the aid of an analytical method. In this method, the objective of placement is to reduce the loss. Firstly, the optimal size of the storage is determined for each busbar in the proposed methods and then, a busbar with the lowest loss level is selected as the optimal busbar. Next, the storage is placed in that location with the optimal value, and the optimal location and capacity of the capacitor are determined in order to achieve a minimum loss.

Reference [27] introduced two PI-PSO controllers to stimulate a DVR for enhancing the on-grid hybrid system under misfire and fire-through faults. The PI-PSO controllers' goal is to force the system voltage at the POT to control the voltage between the DVR and the load and consequently enhance the performance of the system during misfire and fire-through faults. The proposed PI-PSO controller showed a better performance concerning the system voltage, RESs' powers, and the WECS speed, electromechanical torque, and power. The objective of [28] is to design an economic microgrid system for the Yanbu region of Saudi Arabia. This design aims to select the best microgrid configuration while minimizing both NPC and LCOE considering some technical conditions, including loss of power supply probability and availability index. The optimization algorithm used is Giza Pyramids Construction (GPC). To prove the GPC algorithm's effectiveness in solving the studied optimization problem, artificial electric field and grey wolf optimizer algorithms are used for comparison purposes.

Determining the strategy to optimize the performance of energy storage systems is one of the problems associated with the exploitation of these systems. In [29], linear programming is utilized in order to determine the optimal performance of an energy storage system. In this paper, real-time pricing is utilized and the studied system consists of one local manufacturer, the storage, load, and grid. Since the prices are not steady (changing), the profit as a result of energy sale, energy acquired by storage from the grid and manufacturer aiming at charging, and energy supplied to the load by the storage are determined at each hour. In [30], the storage optimal location and capacity are determined aiming at improving the voltage profile. In this paper, sensitivity analysis (SA) is utilized. Simulation is conducted for an IEEE 13-bus system and it is assumed that the grid consists of solar cells. Using the energy storage improves the voltage profile considering the load variation and solar radiation at different times of the day and different seasons.

Flattening the load curve is one of the objectives of use management/control. In this paper, the use of storage is investigated aiming at reducing peak load and flattening the load curve. Considering that gas power plants are utilized in peak load conditions, this paper suggests a substitute solution, namely the energy storage, for these types of power plants. Next, a dynamic programming model is utilized in order to determine the optimal capacity and programming of storage, aiming at reducing the fuel costs of power plants. The unsteady nature of renewable energy resources causes troubles in power grids. Therefore, these types of resources are utilized alongside the energy storage. An economic method for determining the optimal storage capacity is proposed inside the micro-grid. The studies are conducted in two modes, including islanded mode and grid-connected mode. The solver is inspired by integer linear optimization (programming). The results depict that the profit achieved by the micro-grid has increased after installing the storage.

In this paper, the objective is the reduction of peak load by the installation and optimal placement of the energy storage inside the grid and managing the charge-recharge of storage resources. Hence, particle swarm optimization is utilized in order to find the location and capacity of storage resources. Next, a practical and well-rounded program is proposed in order to optimally exploit the storage at

different times during the day. In Section 2, an explanation is given concerning objective function and constraints. In Section 3, swarm optimization is explained briefly. In Section 4, the results of simulations are presented and compared with simulation results achieved by previous literature. Ultimately, a summary of results and conclusion are presented in Section 5.

2 Objective Function and Constraints

Energy storage systems are among the existing technologies considered in creating and developing electricity smart grids. Hence, energy resources can be utilized as one of the impressive strategies for peak load shaving in the grid. The energy storage is one of leading load management methods in power grids. In this method, power plants always generate energy in an optimal condition of their performance and they are not required to follow the load curve. In the case of surplus energy in the grid, this energy is stored in the storage elements and then, supplied back to the grid during peak hours. In other words, storage is the realization of how the load is transferred in the power grid.

Power consumption varies at different times of the day. Considering the unsteady price of electricity at different times of the day, the storage is supplied energy during off-peak hours (low electricity price). Considering the difference between electricity prices for peak hours and off-peak hours, this matter will increase in the grid profit. Taking the above process into consideration, the ratio of loss reduction during peak hours is more than loss increment during low-peak hours. Moreover, installing storage will bear a number of costs. In this paper, the objective is to maximize profit achieved by storage installation. Cost and profit functions are given as follows for one day:

2.1 Investment Cost

The investment costs of the storage include two types of costs, namely (1) power electronic equipment costs and (2) storage unit costs.

The annual cost includes annual investment cost, annual replacement cost, and annual maintenance cost. Annual maintenance cost is calculated as follows [22]:

$$OMC = OMF \times P_M \quad (1)$$

where OMF is maintenance cost per kW. Investment costs include three parts, including power electronic equipment cost, storage unit cost, and the balancing cost (grid-connected mode) of the power plant. The power electronic equipment cost is calculated as follows:

$$PCS = PCSU \times P_M \quad (2)$$

where PCSU is the power electronic equipment cost per/kW. Storage unit cost can be calculated using the following equation [23]:

$$SUC = \frac{SUCU \times P_M \times H}{eff} \quad (3)$$

where SUCU is the storage unit cost per kW (\$/kWh) and *eff* is system output/efficiency, which is calculated as follows:

$$eff = \frac{energy - (kwh) - out - during - discharge}{energy - (kwh) - in - during - charge} \quad (4)$$

Balancing cost is as follows:

$$BOP = BOPU \times H \times P_M \quad (5)$$

where BOPU is the balancing cost per kilowatt-hour (kWh). The total investment cost can be calculated through summation of power electronic equipment cost, storage unit cost, and power plant balancing cost:

$$TCC = PCS + SUC + BOP \quad (6)$$

The annual investment cost can be written as follows:

$$CRF \times AC = TCC \quad (7)$$

CRF is the rate of return (ROR):

$$CRF = \frac{(i_r (1 + i_r)^y)}{((1 + i_r)^y - 1)} \quad (8)$$

where i is the annual interest rate and y is the collection life span. In the case of using a battery in the storage unit, we may need to replace the battery during the life span of the collection. The total annual replacement cost per kWh is calculated as follows:

$$A = F \times [(1 + ir)^{-r} + [(1 + ir)^{-2r} + \dots] \times CR \quad (9)$$

The number of terms in the above equation equals the number of times the battery is replaced during the life span of the collection. R is period of replacement:

$$r = \frac{c}{n \times D} \quad (10)$$

where c is the number of charge-discharge cycles during battery life span. D denotes the number of days in which storage is utilized and n is the number of charge-discharge per day. Annual replacement cost equals to:

$$ARC = \frac{A \times P_M \times H}{eff} \quad (11)$$

As a result, investment cost per day is as follows [23]:

$$COD = \frac{(AC + OMC + ARC)}{D} \quad (12)$$

2.2 Storage Charging Cost

Storage acquires energy from the grid during off-peak hours. This cost equals:

$$C_{charge} = P_M \times H \times \lambda_1 \quad (13)$$

where λ_1 is the electricity price during off-peak hours.

2.3 The Cost Imposed by Increased Loss

As mentioned above, storage acquires energy from the grid during off-peak hours. As a result, the loss increased during these hours. As a result, the cost of such event equals:

$$C_{charge} = (P_{LCharge} - A_1) \cdot H \cdot \lambda_1 \quad (14)$$

where $P_{LCharge}$ is the loss in storage charging mode and A_1 is the amount of loss in the grid during off-peak hours and prior to storage installation.

2.4 The Profit Gained by Energy Sale

During peak hours, storage supplies energy to the grid. Hence, the profit gained by energy sales equals [29]:

$$C_{\text{discharge}} = P_M \cdot H \cdot \lambda_1 \quad (15)$$

λ_1 is the amount of loss in the grid during peak hours and prior to storage installation and C_{charge_1} is the amount of loss during peak hours and after the installation of storage. C is the number of times the storage is charged/discharged during its life span.

3 Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO), better known as bird swarm algorithm (BSA), is a state-of-the-art heuristic technique that is inspired by the behavior of birds' flock in nature. PSO is a powerful stochastic optimization algorithm that is inspired by flock movement and intelligence. In Fig. 1, the behavior of a group of birds or fishes is illustrated.



Figure 1: Foraging behavior of birds and fishes adapted from [18]

This algorithm utilized social interaction for problem solving and was developed by James Kennedy (social physiologist) and Russell Eberhart (electronic engineer). They used a number of particles forming a group and these particles are moving inside the search space to find the best solution.

A particle is considered a point inside the N-dimensional space that regulates its levitation according to its own and other particles' levitation experience. Each particle follows its coordinates inside the solution space that is associated with the best solutions achieved by that particle so far. This value is named best person (P_{best}). There is another value for the neighbor particle that is followed by the algorithm. This value is named best global (G_{best}). In other words, it is considered the best global experience.

The main concept of PSO is the acceleration of each particle toward their P_{best} and G_{best} locations that is executed randomly each time with an accelerator, as shown in Fig. 2. In this Figure, S^k is the current search point, V^k is the current velocity, V_{pbest} is the velocity based on P_{best} , S^{k+1} is the search or modified point, V^{k+1} is the modified velocity, and V_{gbest} is the velocity based on G_{best} .

As mentioned earlier, PSO mimics the movement of birds' flocks. Think about the following scenario:

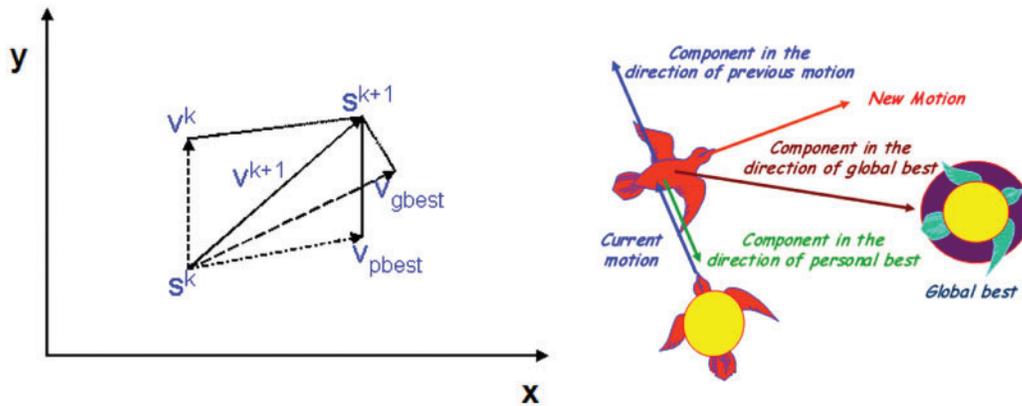


Figure 2: Concept of modification of a searching point by PSO adapted from [18]

A group (flock) of birds are searching for food in an area in a random manner and there is only one portion of food inside the searched area. None of the birds knows the location of food but they know the distance from the food at each stage. Therefore, this problem is about finding the best strategy to find food. An effective method is to follow the birds that are closer to the food. By following such a scenario, PSO is utilized to solve the optimization problems. In PSO, each unit is considered to be similar to the one bird in the search space, which is called a particle as mentioned earlier. Two parameters are defined for all particles as follows.

- The best response (fitness) is assessed and optimized with the aid of a fitness function.
- Velocities in the same direction as particles levitation inside the problem space by following currently optimized particles.

PSO starts with a group of random particles and then, is updated with two optimal quantities. The first one is the best solution (fitness) that is found so far. This quantity is stored and named P_{best} . The other quantity is the best global and is named G_{best} . When a particle considers a part of the population as the location vicinities, the best quantity is transformed to the best location and named P_{best} . After finding the best two quantities, the velocity and location of the particle are updated.

Each particle tries to modify its location with the following data: current position, current velocities, the distance between the current position and P_{best} , and the distance between the current position and G_{best} . They can be modeled with the aid of the following equation mathematically:

$$V_i^{k+1} = w \cdot V_i^k + c_1 \cdot rand_1(\dots) \cdot X (pbest_i - s_i^k) + c_2 \cdot rand_2(\dots) \cdot X \tag{16}$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \tag{17}$$

V_i^k is the velocity of agent i in k iteration, w is the weight function that varies between 0.4 and 0.9. As the parameter becomes smaller, the algorithm tends to converge quickly. Moreover, as the parameter becomes larger, it tends to search the space better for the new solutions.

rand: generates a random and uniform number that is distributed between 0 and 1. S_i^k is the current position of agent i in k iteration.

P_{best} is the best location for agent i , and G_{best} is the best location experienced by the swarm.

c_1 and c_2 are personal and collective (swarm) cognitive coefficients and their values vary between 0 and 2. However, these values are usually considered two. An increase in c_1 and c_2 values causes the

particle to move toward personal best and converge toward the swarm's best experience. The algorithm process is given as follows:

- Creating the initial population (swarm) and assessing it
- Determining the best personal memories and collective memories
- Updating to new velocities and positions, and evaluating the new responses
- Starting from stage 2 if the termination condition is not achieved.
- End

Particles' velocity in each dimension achieves a maximum velocity V_{max} . If the total acceleration causes the velocity to exceed V_{max} , the velocity of that dimension will be limited to V_{max} and the user determines this parameter. In Fig. 3, a flowchart is presented for the PSO algorithm.

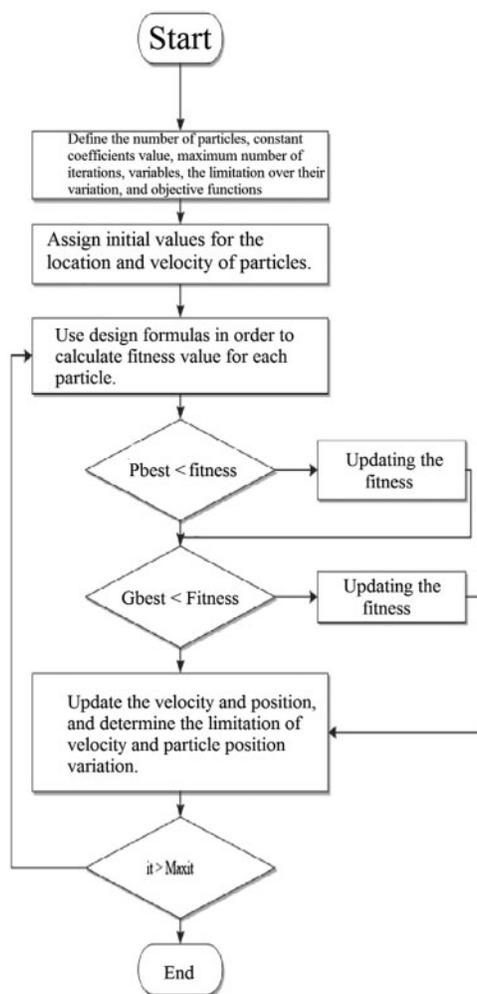


Figure 3: A general flowchart of PSO adapted from [24]

4 Simulation and Result Analysis

In this section, the proposed model to determine the capacity and location of storage and the charge-discharge program of these resources within the system are studied. Using particle swarm optimization, the location, capacity, and storage exploitation are investigated. Such an algorithm enjoys high accuracy. PSO parameters are presented in Table 1. Studies conducted in this field are aiming at decreasing the loss and peak load, increasing and the profit achieved by charging and discharging storage resources.

Table 1: PSO parameters

Population	Iteration	$C_1 = C_2$	w	V_{min}	V_{max}
100	50	2	0.7	0.4	0.9

The grid under investigation includes a standard 33-bus distribution system. In Fig. 4, the single-linear arrangement of the system under investigation is illustrated. This is a radial grid and all the loads are fed through one pass. Active loss of the intended grid is reported to be 210.998 kW.

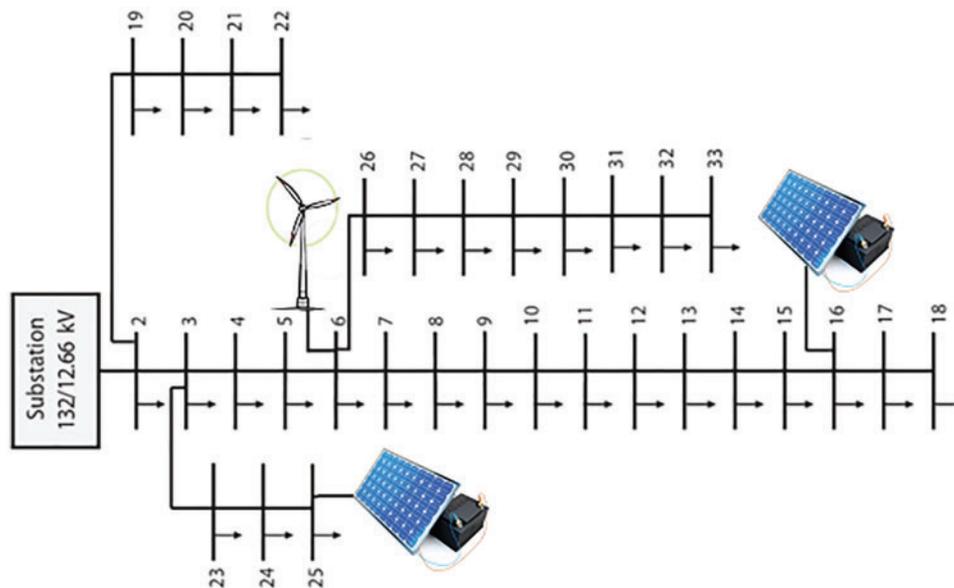


Figure 4: A single line diagram of the test system adapted from [23]

In Fig. 5, the amount of loss in all the lines without the distributed generation resources are presented. The maximum amount of loss is associated with line number 2, which is reported to be approximately 59 kW.

In the grid under investigation, three distributed generation resources are taken into consideration. These three resources are considered in bus #6, bus #16, and bus #25 respectively, with the following capacities: 2.4878, 0.3556, and 0.7291 MW [22]. In this paper, it is assumed that the generation resource in bus #6 is a wind turbine and the other two are solar panels.

The amount of power generated from solar panels and wind turbines depends on the radiation and wind speed. As a result, radiation intensity and wind speed in the location under investigation

should be determined. Radiation intensity and wind speed during 24 h of investigation are shown in Figs. 6 and 7.

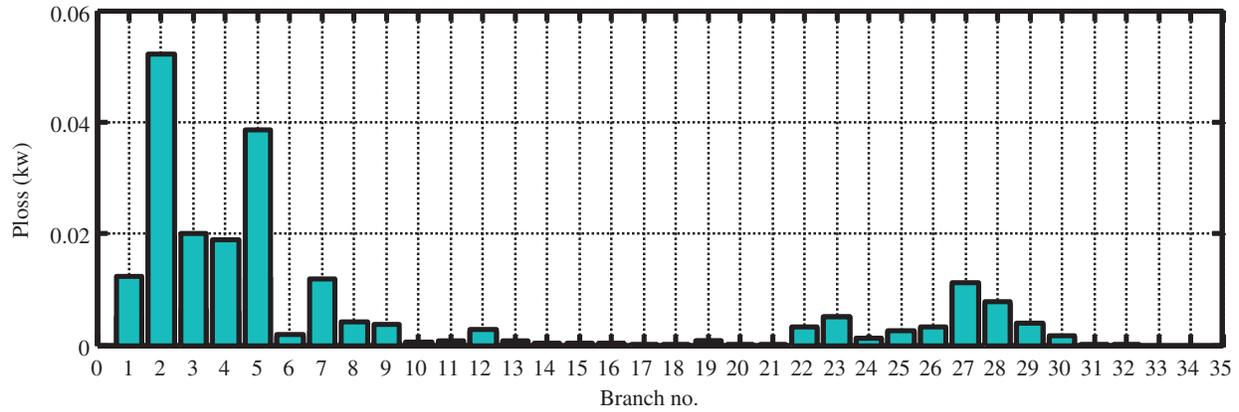


Figure 5: Line losses

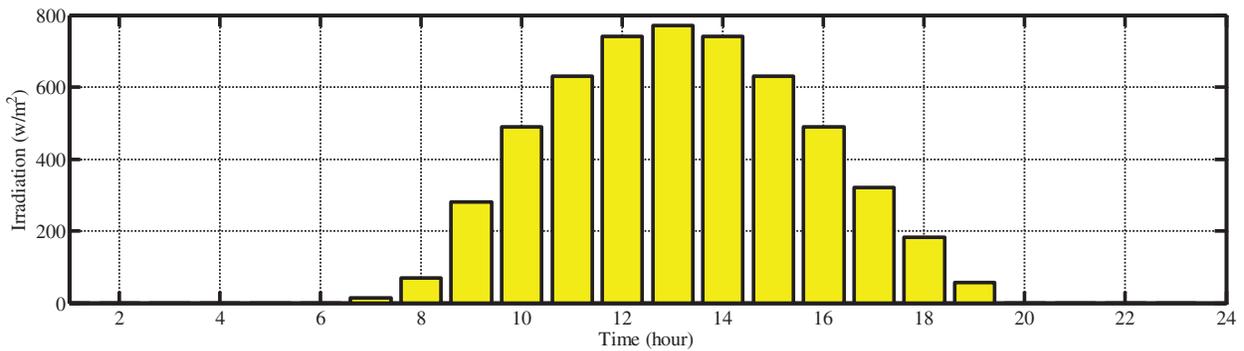


Figure 6: Solar radiation level

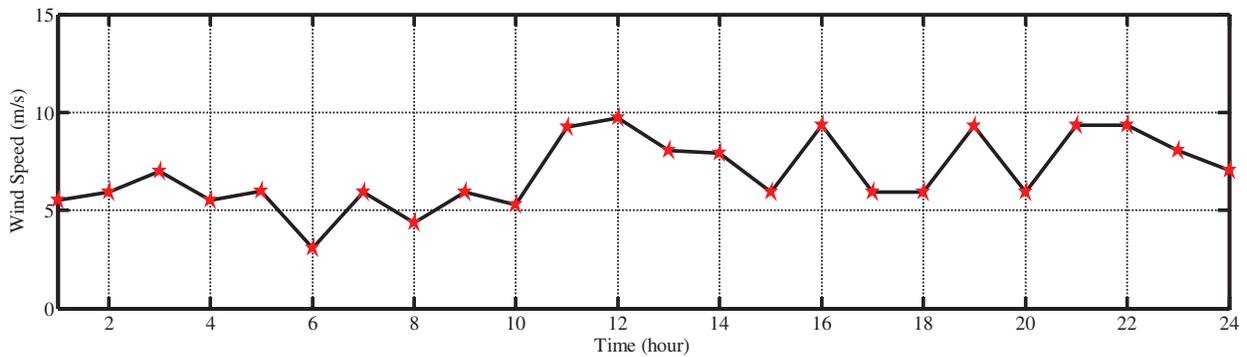


Figure 7: Wind speed

In Fig. 8, the amount of load in the grid during 24 h of investigation is shown using bar graphs in per unit. The amount of power required by the load is less than 0.4 per unit at late night and peak load occurs in around 10. The nominal power of the grid is 4.5 MW.

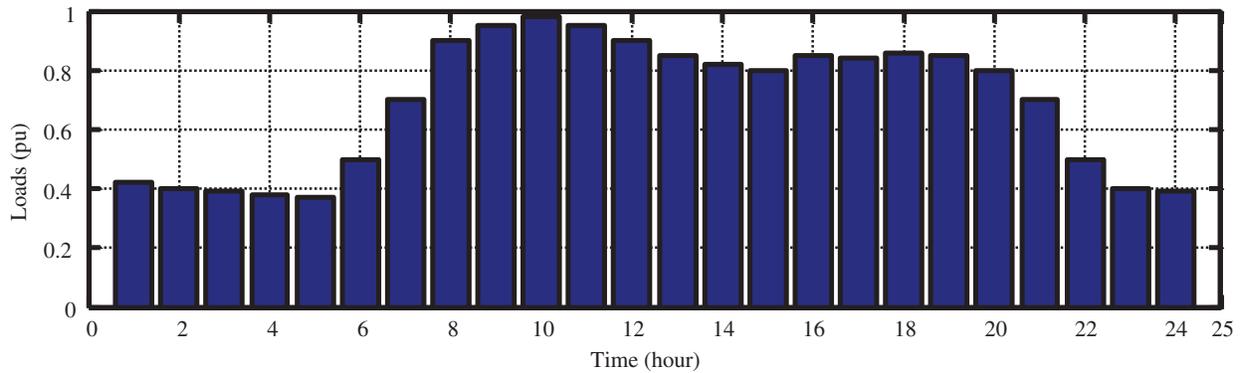


Figure 8: The power needed by load (in per unit)

Two different scenarios are utilized in this paper. In the first stage, the location and capacity of the storage are investigated aiming at reducing loss in the grid. In the second stage, this algorithm is utilized for charging and discharging these resources at the selected points, aiming at flattening the load profile.

4.1 First Scenario

In this section, the location and capacity of storage resources are investigated. In the simulation, it is assumed that only two areas in the grid can be utilized for storage installation and each of these areas can provide a maximum of 70 collections of installable batteries [24]. As a result, each collection of batteries can provide power equal to 7.7 kW. In addition, a maximum of 540 kW can be installed at each storage bus.

Hence, particle swarm optimization has been utilized aiming at reducing loss in the distribution system. Investigation is conducted at 10 am at the time of peak load occurrence. In the case of non-installing the storage, the amount of loss is reported to be 98.2 kW only in the presence of distributed generation resources in the system. In Fig. 9, the amount of loss for each line is presented with the aid of bar graphs.

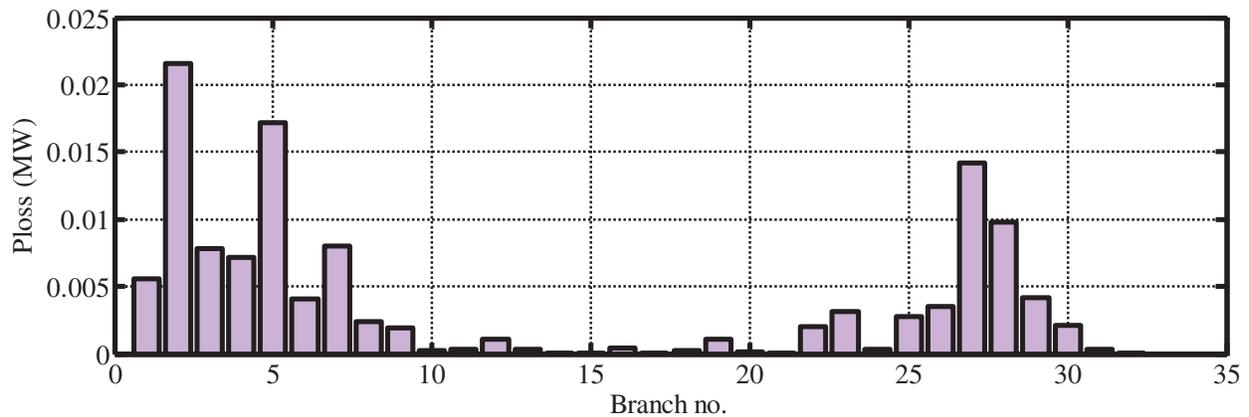


Figure 9: Line loss prior to storage installation

The amount of loss is calculated using the following equations for power systems. If the total power injected into the busbar i is known, the total system loss will be equal to the complex power of all machines [31–37].

$$P_L + jQ_L = \sum_{i=1}^N S_i = \sum_{i=1}^N V_i I_i \tag{18}$$

where N is the number of buses, P_L is the active losses, Q_L is the reactive losses of power system, V_i is the voltage of busbar i , S_i is the power injected to bus i , and I_i is the bus i current.

The proposed objective function is defined as Eq. (18). After the optimization process, the results depict that two storages should be installed in busbar #8 and busbar #23, with the following capacities respectively: 540 and 300 kW/h. In Fig. 10, the variation curve of the objective function (loss) is presented in 50 iterations of the algorithm.

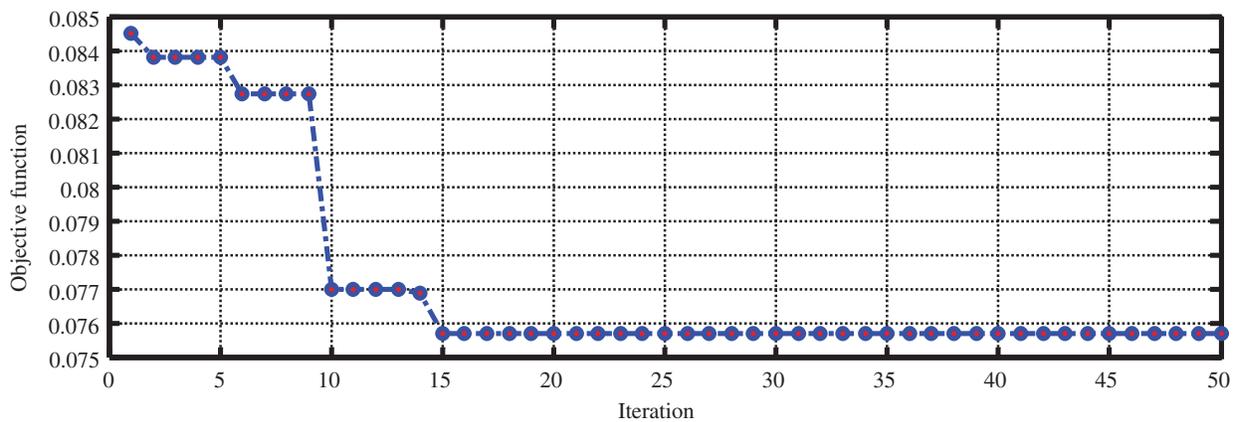


Figure 10: The best objective function value at each algorithm iteration

According to the figure, the amount of system loss has decreased to 75.5 kW after installing the storage is in the selected areas. In Fig. 11, the amount of line loss after storage installation is shown using a bar graph.

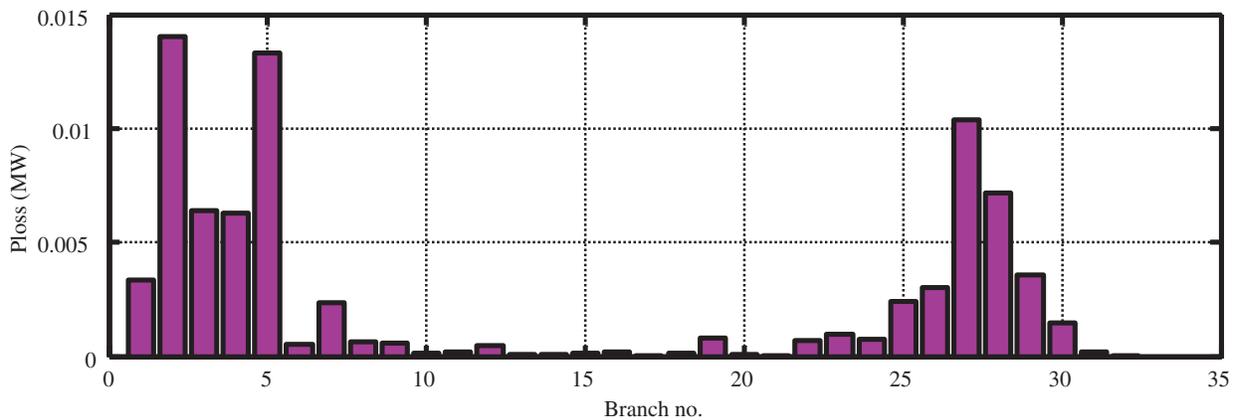


Figure 11: Line loss after storage placement and determine the capacity

A comparison between Fig. 11 with Figs. 5 and 9 illustrates the impact of storage in reducing the loss in all lines. As can be seen in Fig. 11, the loss of most lines has been decreased after storage installation and line #2 accounts for the most loss. Moreover, the amount of loss is reduced to reach one-quarter of the base conditions (non-presence of distributed generation resources and storage). In the next stage, simulations are conducted with the aid of particle swarm optimization in order to improve the load profile and flatten it. Moreover, charging and discharging of storage should be done in a way that the load profile will have the least number of difficulties and we will have an almost linear diagram.

4.2 Second Scenario

The aim of demand response is to reduce peak load in the grid for increasing the capacity of grid spinning reserve and as a result, reduce the need to construct new power plants. Demand response can be utilized in order to reduce the level of electrical power consumption to reach maximum electricity demand efficiency and in this way, many costs can be saved. In a long term, the profit caused by reduced costs can be used to invest in new power plant [38–61]. Due to the establishment of the electricity market, electricity generation costs and electricity sale prices are different at different times of the day. For reducing grid peak load in off-load and medium-load hours (during which a high level of installed capacity is not connected to the circuit), the electricity is stored during off-peak hours (low price electricity) to be used later in peak load hours (high price electricity).

Electricity price varies at different times of the day. This paper provides simulations based on time of use (TOU). This is the most common pricing method and most countries use this method. In this method, hours in a day are divided into several periods, in each of which different prices are considered for energy. The most simple TOU method considers two periods, peak load and low-load (off-peak) hours. In some cases, medium-load hours are also taken into consideration. It is natural that the prices associated with low-load and medium-load hours will be less than peak-load hours. A sample TOU pricing is given in Table 2. The generated power by solar and wind resources are illustrated in Figs. 12 and 13 according to the resources capacity, radiation intensity, and wind speed during the 24 h of investigation.

Table 2: Electricity price during peak load, medium-load, and off-load hours adapted from [25]

Price (\$)	Hours
0.10074	Off-load [22 to 6]
0.28719	Peak load [6 to 14]
0.184	Medium-load [14 to 22]

As a result, the power needed by the upstream grid can be achieved as Fig. 14 by taking the amount of power generated by distributed generation resources and load in the grid under investigation into account.

As can be seen in Fig. 14, significant changes can be seen for power demanded by the upstream grid despite the presence of distributed generation resources. Hence, the storage resources can be utilized in order to reduce difficulties generated in grid power. After the optimization process with the aid of particle swarm optimization with the aim of minimizing objective function (cost), the state of charge (SOC) of two storages can be achieved as Fig. 15.

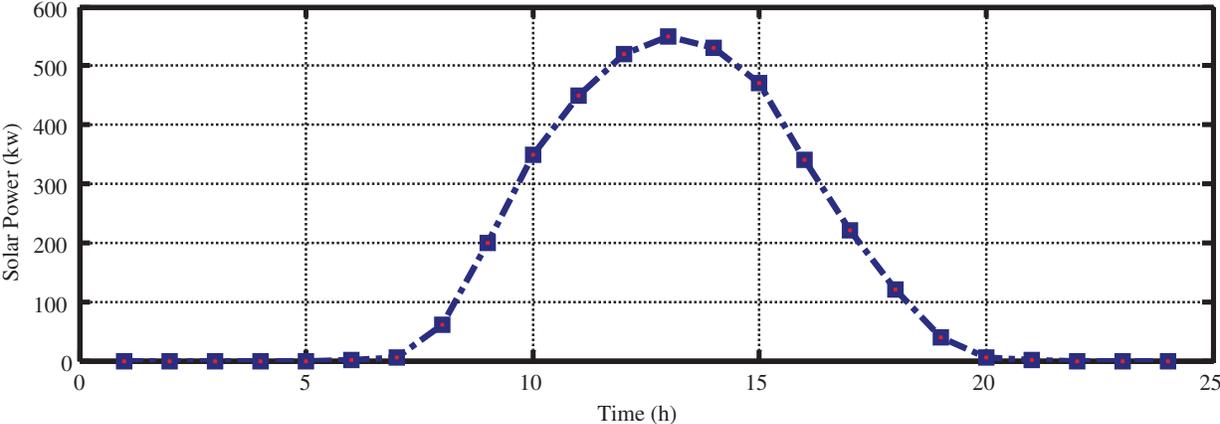


Figure 12: Solar power

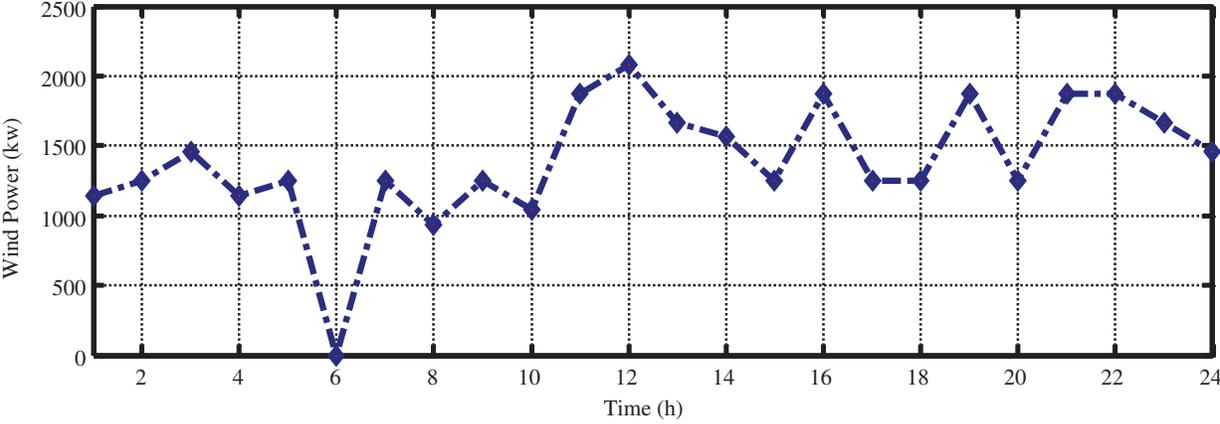


Figure 13: Wind power

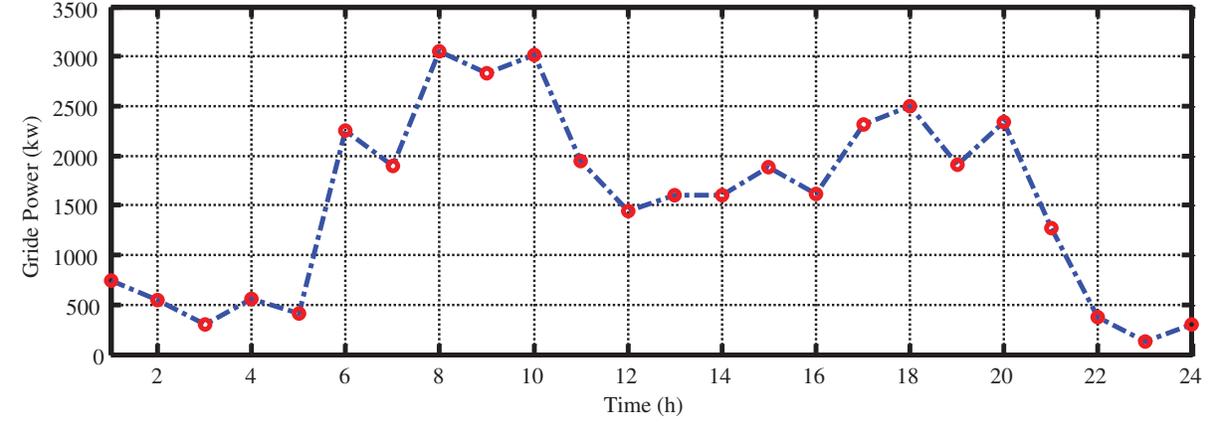


Figure 14: The amount of power demanded by the grid

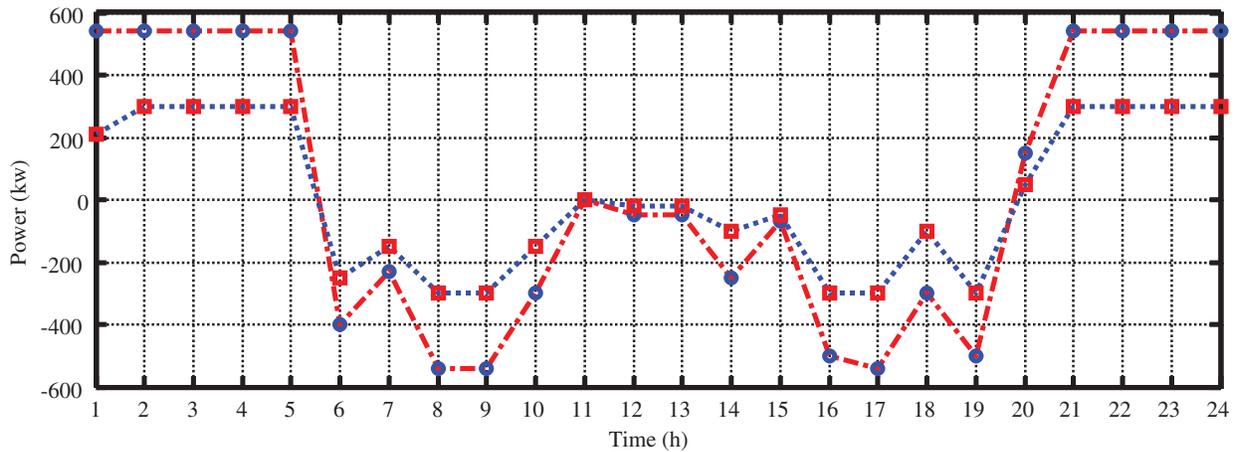


Figure 15: Charge and discharge status of each storage resource

As expected, storages stored energy at the earlier hours of the day due to low prices of electricity and then were discharged during peak load hours (6 to 24) due to increased electricity price. In the second event, the revenue achieved by electricity sales to the grid can help reduce objective function. The charge and discharge status of these two storages are illustrated in Fig. 16 during 24 h of investigation.

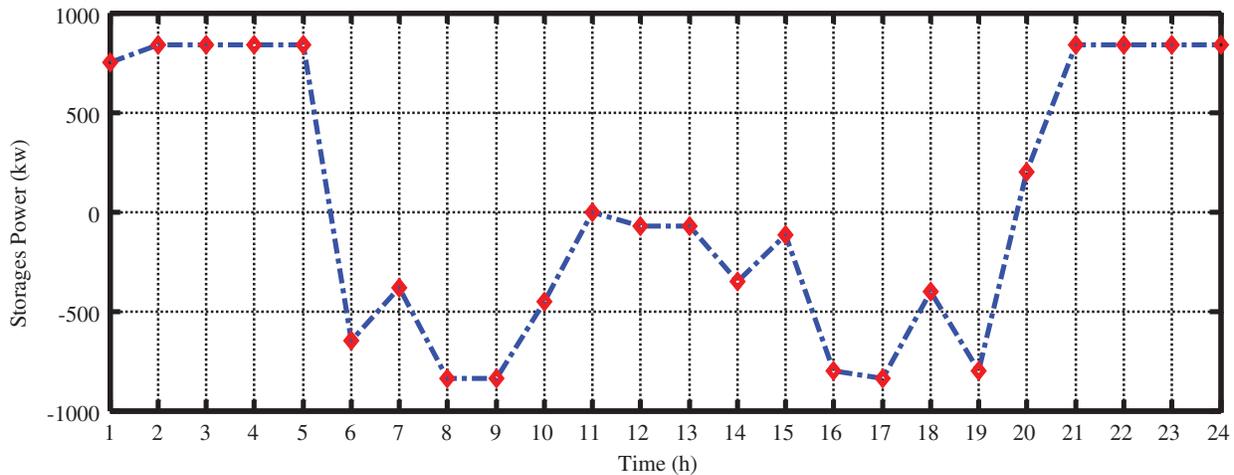


Figure 16: The amount of power exchange between storage and grid

Next, the genetic algorithm was utilized in order to manage storage resources, charge and discharge in the system under investigation. As a result, the charge and discharge status of the storages are achieved as Fig. 17.

The charge and discharge status of all storages are illustrated in Fig. 18.

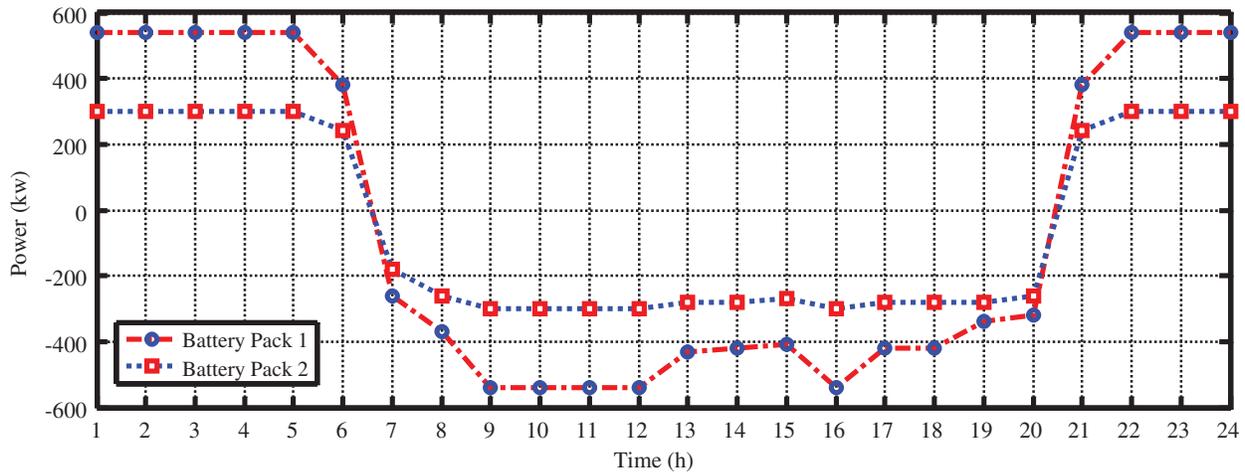


Figure 17: Charge and discharge status of each storage resource

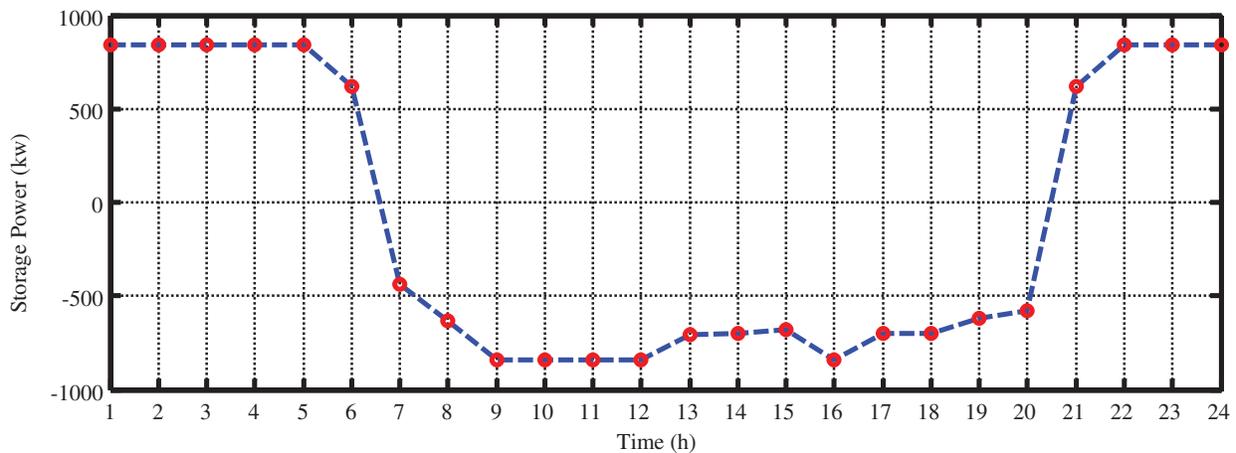


Figure 18: The amount of power exchange between storages and grid

As a result, the power profile needed for the upstream grid was changed as Fig. 19 by considering the charge and discharge status of batteries with the aid of PSO and GA.

According to Fig. 19, the power demanded by the grid has a more suitable status in the presence of the storage resources. During low load hours, the battery is charged as a load in the system. However, the battery is discharged as a power generation resource and this way, it will supply part of the required load. As a result, the amount of power demanded by the upstream grid will be flattened. In Table 3, the results of simulation with the aid of particle swarm optimization are presented. Moreover, the maximum and minimum amount of load and the standard deviation of the grid load are also presented. In addition, in this table, the results are compared with results of the grey wolf optimization algorithm (GWO) and Lightning Search Algorithm (LSA).

The maximum amount of load in the grid is calculated to be 810 by using the storage and managing energy with the help of PSO. However, this value is reported to be 133.33 for the system without storage. In addition, the maximum load for the system with the storage is calculated to be 2568.3 with particle swarm optimization algorithms. However, this value was calculated to be a maximum

of 3052.5. The large difference between the minimum and maximum power demanded by the grid can be seen for the system without storage, compared to the low difference between the minimum and maximum power in the system with the storage. The standard deviation of variation for load demanded by the upstream grid illustrates the minimum changes in the demanded power.

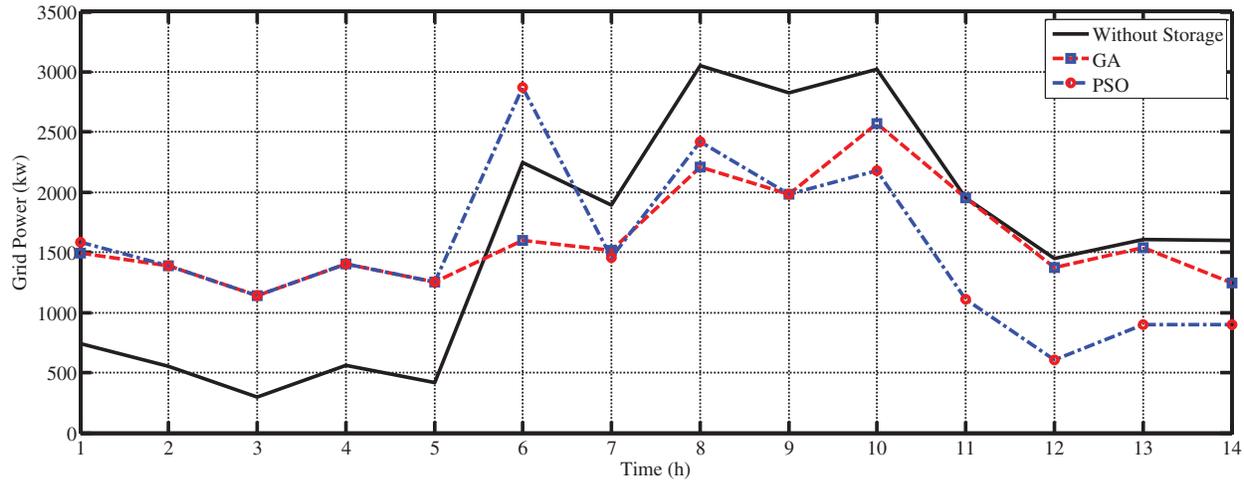


Figure 19: The amount of power exchanged with the upstream grid

Table 3: Electricity price during peak load, medium-load, and off-load hours

	Minimum load	Peak load	Standard deviation
Without storage	133.33	3052.5	925.14
GA	606.66	2868	451.53
PSO	810	2568.3	478.01
GWO	725	2678.2	461.21
LSA	802.33	2486.4	471.21

5 Conclusion

In this paper, placement management, the capacity of storage resources, and energy management of resources are investigated for reducing loss and improving the load profile of the grid under investigation. Optimal installation and placement of the energy storage in the grid and charge-discharge management of storage resources have caused a decrease in peak load. Hence, particle swarm optimization is utilized to find the location and capacity of the storage resources. Simulation results were compared to the genetic algorithm. Ultimately, a well-rounded program is proposed to optimally exploit the storage at different times during the day.

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