Maximizing Social Welfare in Micro-grids to Provide an Smooth Daily Load Profile Using Nonlinear Programing at Scheduled Operation

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Abstract-Micro-grids are consisted of some interconnected networks such as distributed energy systems (resources and Loads) which are able to operate in gird connected and islanding modes. According to different loads in terms of feeding priority, consumers can help Micro-grid control center (MGCC) to do their best optimized scheduled operations. Then it could provide power for critical loads by controlling interruptible loads or displacement of load at different prices . Demand response (DR) plays an important role at electricity market in order to balance power generation and demand level required. Overall consumer pricing can be very useful in reduction of the operating costs, especially when market prices are high. In addition, by using this method, consumers can reduce their payment for less important loads. In this paper, the optimal operation of micro-grid in presence of demand response will be investigated in order to increase social welfare and flattening the load curve at an acceptable level. Multi-objective optimization problem will be solved by Epsilon limitation method with nonlinear programming (NLP) using General Algebraic Model System (GAMS) software package. The proposed algorithm will be implemented on a 17 bus micro-grid. The results indicate that proposed algorithm has ability to improve of micro-grid performance in scheduled operations.

KeywordsDaily Load Profile , Maximizing Social Welfare, Nonlinear Programing, Scheduled Operation.

1. Introduction

Energy resources limitation and growing demand for electric energy, are some major challenges for developing countries. According to these, efficient use of energy resources is so vital. In conventional method (regardless of demand response) loads should be provided over any amount and time, while modern method states so that if the variation will be as low as possible, the system will perform at its maximum efficiency. Since the infrastructure development of power system needs so much payment , demand response is one of the cheapest methods for power system optimal operation in new structure. After restructuring of the electricity industry, demand response programs has been considered for several reasons such as the reduction of peak power, avoid rapid price changes in electricity market and increase the efficiency of power system and energy market .

Energy Association of America is defined demand response as follow: Change in energy consumption of consumers, to respond to change electricity price over time or economic programs designed encourage less use of electricity at a time when market prices are high or the reliability of the network is in risk [1] .so , study about the comprehensive demand response program can be very useful according to maximization benefit of the actors in electricity markets and reasonable pricing of electrical energy during peak hours and off-peak hours of power consumption.

In reference [2], different scenarios of demand management (modeling dayahead market) has been discussed at the level of the micro-grid in presence of consumer pricing in critical and non-critical priorities. In reference [3], a centralized market clearing price mechanism, is recommended in order to notice load handling behavior of price-sensitive consumers. Participation of Consumers that are responsible to price, not only reduces its own energy supply costs, but also due to relocation these expensive hours to cheap hours and thus reduce the energy cost at these hours, will reduce costs for other consumers. In reference [4] , the use of electricity pricing in domestic part has been evaluated in support of influential wind energy production. The basic idea is for low-wind periods when the only heat production exists, and predicted load will be close to supply capacity, Then real-time price signals are so much that will be resolved with DR. Reference [5] offers a complicated algorithm for solving optimization operation where the objective is to minimize the production cost, and is a storage initiative scenario where electricity prices vary in different time periods. The authors in reference [6] have proposed an optimization model to set hourly load level or specific consumer in response to hourly electricity prices. The purpose is to raise consumer welfare by reducing energy consumption levels, limits on the levels of hourly load and linear constraints on load levels.

In [7] where demand response uses real-time pricing model, purpose is to minimize energy costs with a set of linear constraints such as the electrical energy amount required to achieve production target, restrictions on energy consumption in one hour. The authors in [8] perform mathematical analysis of side effects on a 3-bus power system, far from the desired result of reducing electricity local price. importance of plant cogeneration and demand reduction programming to create a competitive market is emphasized in [9]. Optimization problem based on the power cost generation that contains total costs of production andDR . Restrictions on the generators capacity and demand drop , reducing overall energy in hands of a bidder and balance between supply and demand has been programmed over each period, but this text failed to solve the network performance limits. In reference [10] the authors proposed a method to select the optimal DR points , along their capacity to achieve goals such as maximizing the available transmission capacity (ATC), minimize unsupported energy expected (EENS), minimize active power losses and minimize the overall program demand response capacity. Due to such goals that are uncoordinated, there is an algorithm to obtain the optimal Pareto answers. In [11] the evaluation of demand response effects on system changes, such as the overall cost of energy and market-clearing price is done with Unit Commitment. Reference [12] has discussed on the feasibility of reliability on the basis of programs other than price-based programs. Reference [13] examined several issues related to two models of demand response that include demand response based on reliability and demand response based on price. This article mentions that none of them lonely cannot maximize the DR benefits. Reference [14], offers a series of useful DR principles and concepts, for any fields about power and energy customer management. In [15] a method was suggested for solving the problem of minimizing energy cost to calculate the optimal time energy consumption of some customers that are serviced by one grid electricity. In other methods, optimization problem is solved centrally and so customer consumption levels are controlled centrally that requires high-level connection between the company and customers. Here, the authors suggest an energy consumption programmer that is able to connect with smart measuring at any point, to solve the optimization problem locally and automatically using a method of game theory. Reference [16] has proposed a method demand response named event (emergency), having a particular type of system possibilities, especially using reductions in load and objective function , the goal is to detection operational resources to achieve a desired level. The authors in [17] propose modeling and simulation of commercial building loads, especially air conditioning loads to estimate the margin for controlling certain load. This architecture consists of a central controller that calculates the optimal control in accordance with limits and also calculates the planned control strategies in local controller at energy management system related to any consumer building. In distribution network, losses reduction by shifting load using demand response is presented in [18]. Reference [19] is deal to manage micro-grid with common control electronics interfaces. In the method, intermediaries control the main part of the network and exploit the distribution of active and reactive power as well as improving energy efficiency in island state. In [20] a new pricing algorithm to reduce the peak-to-average load demand was provided.

As regards review of the resources, demand response programs are to maximize social welfare , On the other hand, one of the main exploiter goals is smooth the load curve. Therefore, innovations obtained over this research are the optimization joined with social welfare and flatting the load curved before demand response. Multi-objective optimization problem, using restriction method (Epsilon) as a nonlinear program(NLP) will be offered. The proposed algorithm will be implemented on a sample micro-grid 17 buses in (GAMS) software. Various scenarios are discussed in this article are:

- First scenario: micro-grid exploitation in normal mode without demand response
- The second scenario: micro grid exploitation in small island state without demand response
- The third scenario: : micro grid exploitation in small island state with demand response.

In the secondpart of this text , modeling of consumer pricing, model based on single-objective functions of social welfaremaximization, minimizing daily load offset vs the mean value and finally multi-objective model inside a micro-grid will be investigated and also in part 3 some offered studied scenarios.

2. Modelling D. A. Market in Presence of Critical and Non-critical Loads

Modelling day ahead market includes production and consumption pricing in presence of critical and non-critical loads and the main goal is to maximize social welfare. Market operator must perform a multi-period optimization program to determine production plan and optimized consumption and also market-clearing price π^t at any period. It is supposed that the final producer unit can be used to balance the market. An extra payment is added to final production unit cost to determine market-clearing priceπ^t. This extra payment allows final manufacture units to make-up no-charge cost (A fixed cost manufacturer units incurred regardless of production level) and start-up cost (a fixed cost manufacturer units incurred while Concurrence). Participation in the next day market, allow consumers an opportunity to adjust their activities.To discuss about consumer pricing impact, consumer surplus price and social welfare should be noticed objective function. consumer pricing Method is price- power suggestion for different load priorities. The procedure is shown in Fig. 1. Based on this figure, Consumer is ready to consume α load proportional his total load on π_{NonCrt} price or less and for his critical load part is ready to pay maximum π_{Crt} per kilowatt-hour.

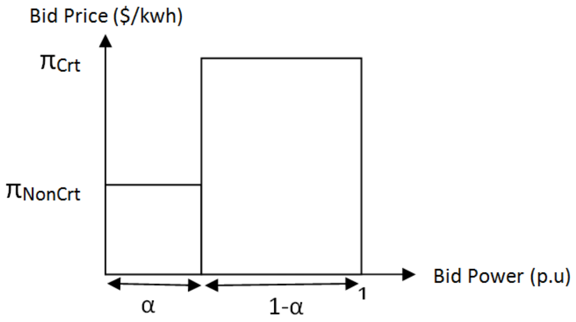

Fig. 1. pricing of load types

3. Objective Functions

There are three objective functions which are discussed below:

- *The First Objective Function: Social Welfare Maximization*

Consumer surplus price and operation cost , are defined as follow:

$$GR^t = \sum_{b=1}^{B} \sum_{Load\in\{Crt,NonCrt\}} \pi_{Load}^{b} . D_{Load}^{b,t} \tag{1}$$

And

$$Cost^t = \sum_{g=1}^{G} C_g(P^{g,t}) \tag{2}$$

Where GR^t is the total gross of consumer surplus at time t of exploitation, π_{Load}^{b} is consumer suggested price for each type of application time, $Cost^t$ Total operating cost per hour 't' and $C_g(P^{g,t})$ is Operating cost function of g'th generator.Thus, the first objective function (Obj_1) that is the same as the maximization of social welfare is as follows:

$$Obj1 = Max\,\{SW = \sum_{t=1}^{T} (GR - Cost^t)\} \tag{3}$$

While

$$Cost^t = \sum_{g=1}^{G} C_g(P^{g,t}) \tag{4}$$

And the constraints are:

$$\begin{cases} P_G^{b,t} - P_D^{b,t} = \sum_{b'=1}^{B} \theta_{bb'}^{t} . B_{bb'} \\ \sum_{Load\in\{Crt,NonCrt\}} D_{Load}^{b,t} = P_D^{b,t} \\ u^{g,t} P_{min}^{g} \le P^{g,t} \le u^{g,t} P_{max}^{g} \end{cases} \tag{5}$$

Which $P_G^{b,t}$ is power injection to bus 'b' in time 't', $P_D^{b,t}$ is net power consumption at bus 'b' at time 't', $\theta_{bb'}^{t}$ is phase difference between bus 'b' and b' at time 't', $B_{bb'}$ is admittance between bus 'b' and b', $P_D^{b,t}$is power generation by generator 'g' at time 't' and $u^{g,t}$ is binary variable which shows generator status at time 't' (generator is off or on).Constraint (5) respectively is load flow, power consumption at each bus at each time and power generation limit for generator.In scenarios that consumer participation is not considered, objective function is operation cost minimization.

- *The Second Objective Function: smoothen the load profile*

This objective function (Obj_2) reduces difference between daily load curve and daily average load curve. Demand response can smoothen daily load curve as much as possible. We can flatten the curve more if replace objective function that is social welfare maximization instead of follow function that is total difference with daily average load . In general , we can define this function as follow:

$$Obj2 = min\left[\sum_{t=1}^{T} \left|D_t - D_{avg}\right|\right] \tag{6}$$

Since we used absolute function above, the supposed model will be nonlinear, then to linearize it we have:

$$\begin{cases} Dev_t^+ - Dev_t^- = D^t = D_{avg} & ,\forall t \\ D^t = \sum_{b=1}^{B} P_D^{b,t} & ,\forall t \\ 0 \le Dev_t^+ \le y_t.Dev_{up} & ,\forall t \\ 0 \le Dev_t^- \le 1 - y_t.Dev_{up} & ,\forall t \\ y_t \in \{0,1\} & ,\forall t \end{cases} \quad (7)$$

Thatthe parameters of this equation are:

Dev_t^+: Load deviation from load average in positive direction.

Dev_t^-: Load deviation from load average in negative direction.

y_t : Binary variable shows load deviation from average value.

Dev_{up}:Upper limit for load deviation from average value.

By adding these constraints, our model is being linearized carefully.

- *The Third Objective Function: multi objective function*

In general in solving optimization problems with multi objective function (Obj_3) ,we can't find a particular answer which optimize all objective functions at the same time. so a collection of answers will be found for these problems called Pareto optimal (Non dominated optimal).each Pareto optimal, optimize one function however at least one of the other functions is not optimized.In order to solving problem with ε constrain method one of the objective functions is considered as main objective function and the other functions are considered as constraints for optimization problem. To apply ε constrain method, variation range should be specified for objective functions $Obj_2$to Obj_P and define a particular value for e_2 to e_p. There is a recommended method to calculate these variations that is refer to final result table, it would be investigated follow , So we have:

$$\begin{aligned} &Minimize Obj_1(x) \\ &\text{s.t.} \\ &Obj_2(x) \le e_2, \dots, Obj_p(x) \le e_p \end{aligned} \quad (8)$$

4. Demand Response Model

We consider that the ratio of load on price variation is going to be load participation factor (LPF). As it is shown in Fig. 1 this definition is being clear.The proportion of the demand that responds to prices affectsthe shape of the demand curve. Figure 2shows how this has beenmodelled. Considering the parameters of the demand curveshown on this figure, the load participation factor is defined asthe ratio of the price responsive demand to the total possibledemand:

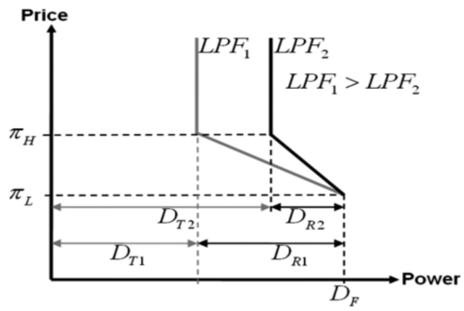

Fig. 2. Relations of LPF and demands

Then we have:

$$LPF = \frac{D_R}{D_F} \quad (9)$$

The parameter DF changes at every period to reflect the natural evolution of the load. On the other hand the load participation factor (LPF) and the parameters π_L and π_H remain constant over the scheduling horizon. The price elasticity of the demand is given by [17]:

$$\epsilon = -\frac{\Delta D}{\Delta \pi}\frac{\pi}{D} \quad (10)$$

It can then easily be shown that

$$\epsilon = -LPF\frac{\pi_L}{\pi_H - \pi_L} \quad (11)$$

It should be noted that the own price elasticityϵ derived in (11) is not the full demand elasticity if demand shifting is taken into account.

5. Performance Index

Because consumers can shift their load from one period to an-other, demand response affects the profiles of prices and loads over the entire optimization horizon. On the other hand, if the bidding price of a consumer is too low, it may not be possible to shift the corresponding portion of load. The assessment of the benefits of demand shifting must therefore be done taking these facts into account. Conventional economic indicators such as consumer surplus are useful in measuring the total benefits of consumption. However they do not indicate how much benefit is obtained if an additional MWh is consumed. Therefore, this paper proposed the calculation of average prices over the scheduling horizon, weighted by the energy consumed or produced at each period. One could use an average market clearing price defined as the average of the market-clearing price at each period π^b :

$$\pi_{avg} = \frac{1}{T}\sum_{t=1}^{T}\pi^t \quad (12)$$

However, because of demand shifting, the cost of an additional MWh of energy for price-responsive bidder is better represented by the following weighted average:

$$\mu = \frac{\sum_{t=1}^{T} X^t \cdot Y^t}{\sum_{t=1}^{T} Y^t} \tag{13}$$

Where X^t represents a series of costs or prices and the weighting Y^t factors are the energy consumed or produced at the corresponding periods. So the Average marginal cost of demand responses is obtained as:

$$\mu_R = \frac{\sum_{k=1}^{K}\sum_{t=1}^{T} \pi^t \cdot D^{k,t}}{\sum_{k=1}^{K}\sum_{t=1}^{T} D^{k,t}} \tag{14}$$

And the Average marginal cost of generators is:

$$\mu_G = \frac{\sum_{i=1}^{I}\sum_{t=1}^{T} MC^{i,t} \cdot P^{i,t}}{\sum_{i=1}^{I}\sum_{t=1}^{T} MC^{i,t}} \tag{15}$$

The benefit or loss that demand response creates for a particular group of participants can be measured by taking the difference between the weighted average prices or costs without and with demand response:

$$\lambda(LPF) = \mu(LPF = 0) - \mu(LPF) \tag{16}$$

6. Studied Micro-Grid Definitions

The micro grid under consideration as shown in Fig. 3, is a low voltage system that feeds domestic, commercial and industrial loads. This micro-grid uses some out speared producers consists of a wind turbine, a micro turbine, a fuel cell and 5 PV .The majority of required load is purchased at upstream network which is power market . Let's suppose that all DGs perform on unity power factor and do not absorb or produce any reactive power. Energy cost purchased from wind and solar units equals their operational cost which is zero. The other properties of units are as follow shown in table 1. The properties of different scenarios under study has been added to appendix 1.

Table (1), properties of DGs.

Unit No.	Name	Min Capacity [kW]	Max Capacity [kW]	Price [Ect/kWh]
1	MT (Micro Turbine)	6	6	4.67
2	FC (Fuel Cell)	3	60	3.4
3	WT (Wind Turbine)	-	3	0
4	PV 1	-	6	0
5	PV 5 to 8	-	5	0

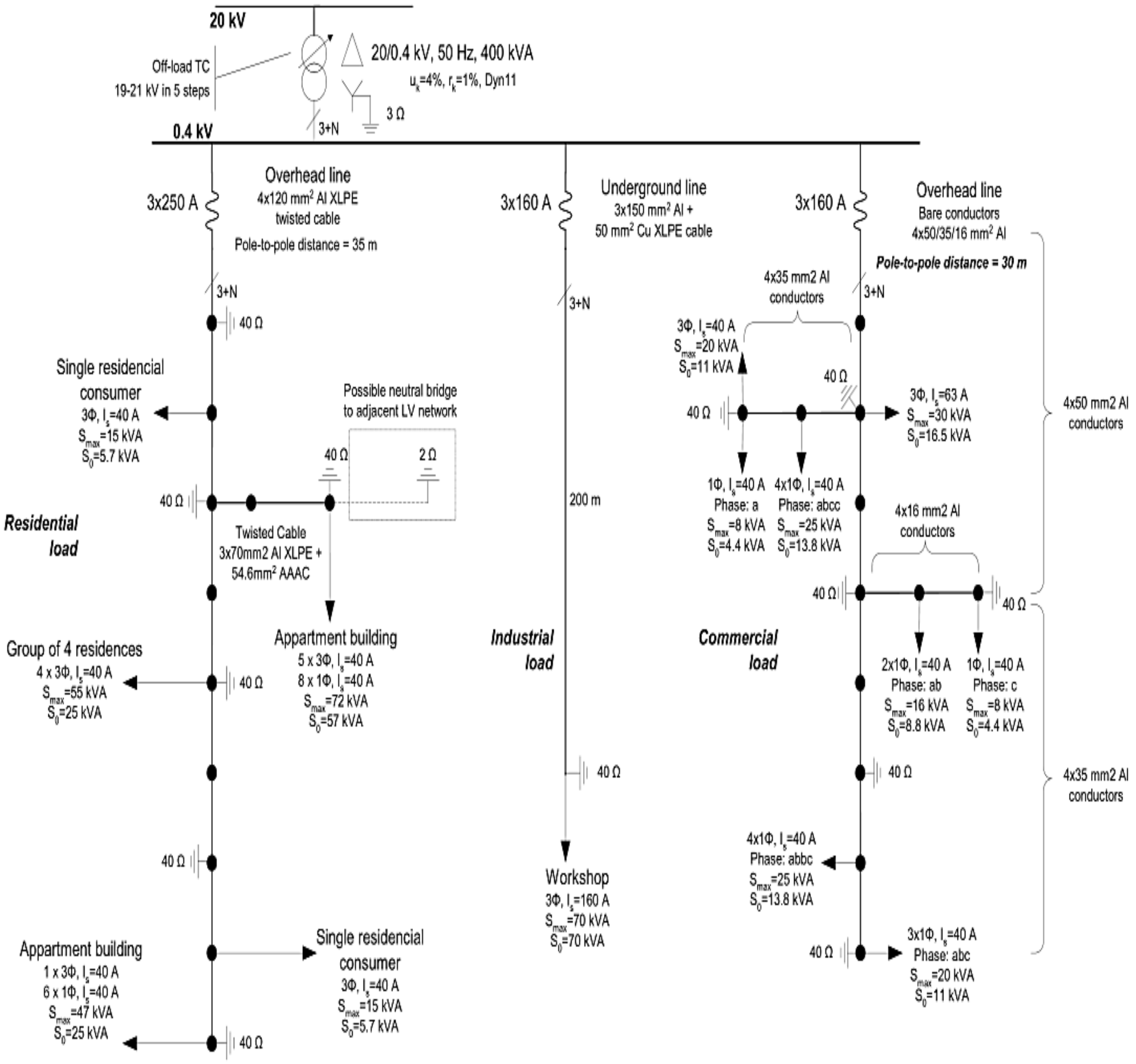

Fig. 3.the considered micro-grid [21].

This micro-grid data has been gotten from [21];Because this reference is one of the most complete one of all.

7. Scenarios

The First scenario is basic mode of operation.in this mode objective function is defined as needed energy cost minimization.in this scenario consumer does not bid and operational cost is calculated according to linear function of each generator production cost. In the second scenario an event cause micro grid being separated from upstream network and works in island mode. It has been supposed that the event occurs at the first working period and micro grid is modeled in island form all the periods. because of local generators limitation, part of load can't be fed in this mode. In the third scenario we consider consumer bidding effect on operation in island mode. This scenario is divides into some sub-scenarios. Each sub-scenario indicates consumer participation level in demand response so that increasing number of these scenarios cause increasing load participation factor in load shifting.

8. Simulation Results

For studding different scenario effect on micro-grid operation simulation results divide into 3 categories :

- not supplied Critical energy for the whole period;
- critical load shedding at each hour;
- load supply average cost;

Figure 4 shows the impact of increasing participation of actors. As it could be seen, the need of load on peak hours is shifted to low load hours. This makes the load profile more smooth. It shows that the DR program comes helpful to the DISCOs or retailers. Then the price in peak hours goes cheaper than previous.By the way, more participation of actors to Demand Side Management can clarify this effect better.

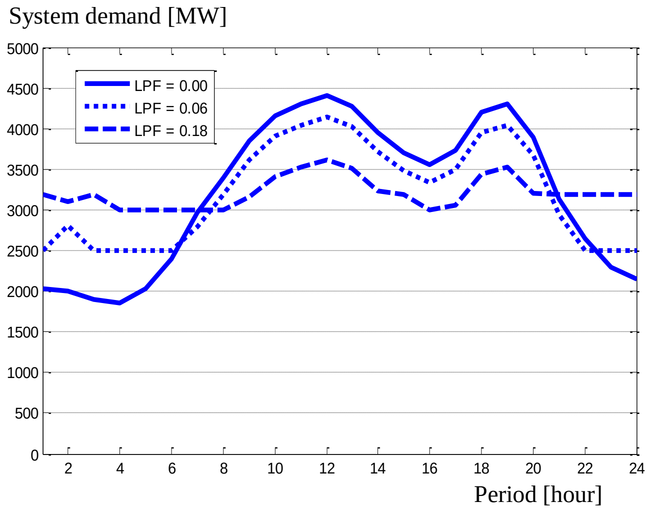

Fig. 4. Load profile of micro-grid

In Fig. 5, we could observe the variations of load demand in 24 hours per a day. It represents that demand variations in initial hours (low electricity prices) is positive. In other word, the consumption is higher when the price is low. So when this happens, more actors encourage to participate the DR program and this issue, makes the MCPs and LPMs lower than previous. Thus social welfare is gone higher. It can be seen in Fig. 6.

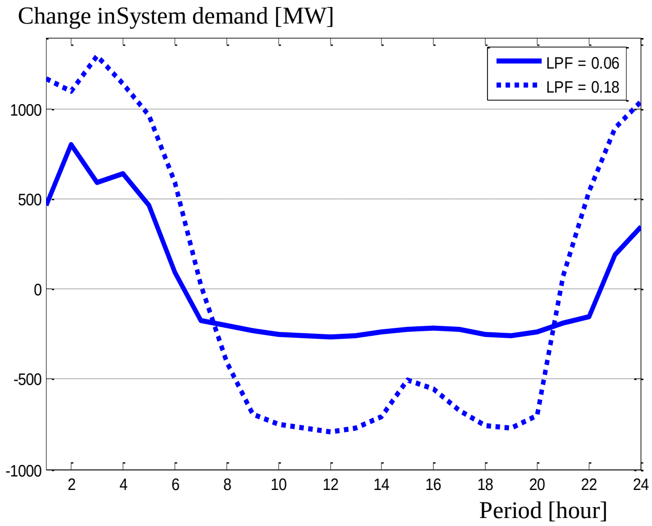

Fig. 5.variations of load profile

Figure 6, shows the impact of increasing participation of loads on Market Clearing Price (MCP). Decreasing of load demands in peak hours, cause the prices getting low. We know that demand response will become more important as electricity prices rise due to fuel price increases, the need for new generation and distribution, and some of the price increases that have come from unfreezing prices after deregulation. Investment in expensive new capacity can be obviated by DR and MCPs can be lowered. By the way, in Fig. 7, the variations of MCP of micro-grid is depicted carefully. This represent that while the actors participate more and more, the MCP changes more correspondingly.

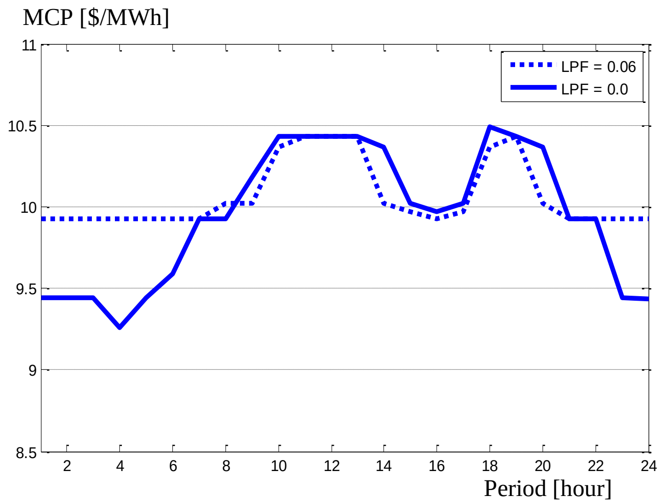

Fig. 6.MCP of micro-gridderegulation market

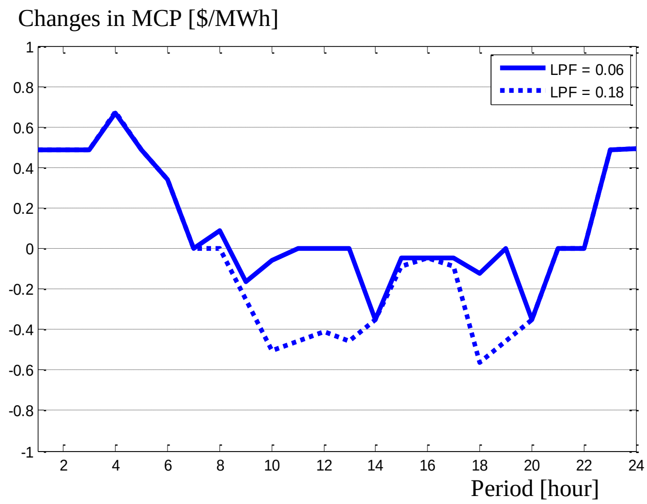

Fig. 7.variations of MCP of micro-grid market

Figure 8, shows critical load shedding level at each hour in island mode scenario without DR and also in island mode consumer participating with DR , we do not have any load outage at initial hours , because just a little load is requested . notice that during high-consumption periods , load outage increases such a high level that reaches almost half of the total requested load. consumer participation at DR and relocation or non-critical load outage causes critical load outage.

Load Shedding [kW]

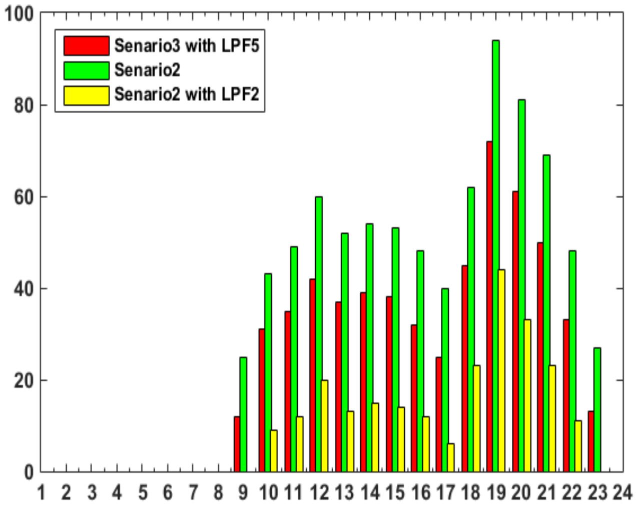

Fig. 8.critical shed load at each hour

Figure 9 shows not-supplied critical energy per kilo-watt-hour for any scenario. In the second scenario, since there is not any consumer participation in DR, not-supplied critical energy is too high, while increasing consumer participation in DR, decreases that one. Indeed as we increase DR, consumers would be able to let network exploiter to relocation or non-critical load shedding, by the way exploiter can feed much more critical load.

Figure 10, shows energy supply average cost per kilo-watt-hour at total set. to calculate this cost, we have just consider consumer supplied energy cost, regardless of not-supplied energy cost. If we want to perform in island mode and increase consumer participation, so energy supplying average cost will increase and that is because critical energy supplying level will increase and non-critical energy supplying level will decrease. In other word, since we increase consumer participation, some parts of non-critical loads (that have cheap supply cost) will be shed and critical loads (that have expensive supply cost) will be relocationed instead, thus total energy supplying average cost increases.

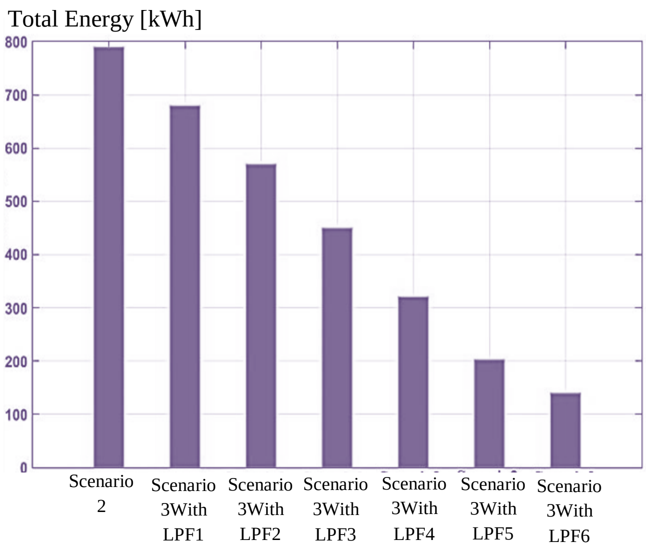

Fig. 9. Amount of critical load not fed at each hour

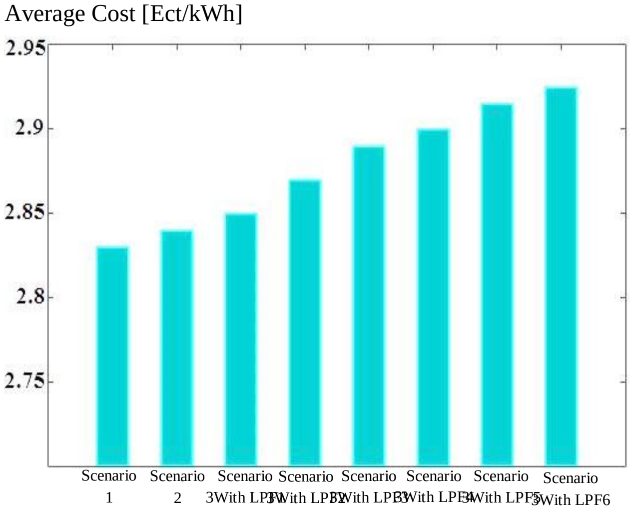

Fig. 10. Average energy securement cost

Figure 11, shows dailyload consumption in 3 states :

- Base mode
- Using DR
- DR considering objective function as smoothen load curve

As it is shown in Fig. 11, difference between the basic load curve and the other load curves is load ascend at some hours and load descend at the other hours .since at the most-consume hours either day or night, the energy cost is too much, so this model decides to decrease consumption level during these hours that are shown at DR curve and smoothen curve Figures. As load reduction in these two curves is the same and have matched each other at day and night middle hours, but in these two curves , load relocation is completely different because of their objective functions nature . notice the curve, DR (multi-pointed curve) is total welfare maximization relates to connection cost minimization directly.

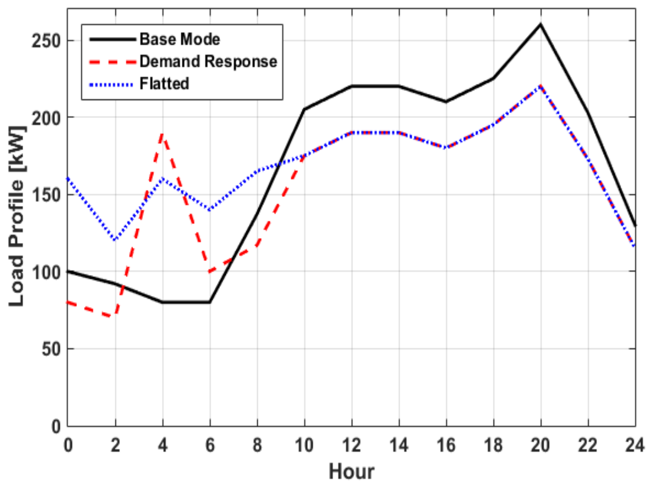

Fig. 11. Daily load profile of considered micro grid

In other words in this mode, model is going to decrease the cost. Since energy cost is minimum value at 4 & 5 o'clock, all of demand responses decrements are shifted to these 2 hours and Load increases deeply at these two hours so that a peak is formed at these hours. Studied system is a small size Micro grid connected to upstream network also it is much more smaller than upstream network . So intense load increment does not effect on upstream network price and micro-grid already is valued particularly.

In operational point of view, though in this mode costs decrease and social welfare increases but it is not desirable because we need a sudden huge amount of applied energy with steep slope of consumption energy increment in these hours . This problem would be solved sortable if we define objective function as load curve smoothen . As it is shown in the third curve (the dotted curve), in this mode load is shifted from expensive hours to those which have low price . Notice that in some hours (6-10) load curve matches the average value and at the other else (1-6) difference between load curve and average value decreases. Advantage of this mode vs the others is difference reduction between peak and valley and load increment slope reduction due to DR . In this mode energy consumption cost is more than previous one because the whole energy capacity does not consume during these hours.

In table 2 objective function values in optimization are considered as single objective function. In social welfare maximization mode, objective function value is 14818.653 which value decreases to 14535.440 during minimization of second objective function. in other words load curve smoothen and load deviation reduction from its average value to 422.188kilo-watt-hour, costs 283.213 cent. A Simple calculation results that load curve smoothen cost in comparison to total social welfare is low about 2% . This 2% decrement in social welfare causes 44.6% load deviation from average value. Considering this notable effect, we can conclude that operation with DR objective function consideration with smoothen is much more effective than DR objective function. So demand response is a promising techno-economical solution to make electricity demand more flexible, allowing private customers to modify their demand profiles to fit the needs of energy supply. In the demand response paradigm, electric utilities provide some sort of incentive to their residential customers as a compensation for their flexibility in the timing of their energy consumption. Utilities also provide a signal to their customers (typically electricity price) that is intended to guide the power consumption so as to obtain an aggregate demand that better matches the needs of the power generation. Demand response has proved effective at shifting consumption away from peak hours, thus increasing system efficiency and stability, reducing the need for investment in peaking generation, and bringing several environmental and financial benefits. So it's good to express that load shifting must be implemented to the load profile to make it flat. According to this, in presented paper we assume that load shifting is occurs at early hours of the day. Then the goal of this paper is to influence consumers to change their demand, in response to the needs of the supplier.

Table 2.value of objective function during optimization

optimization as single objective function	Maximizing F1	Minimizing F2
Total social welfare (F1)	14818.5	14535.4
Load deviation from average value (F2)	945.3	523.0

9. Conclusion

This paper proposed a new framework to solve scheduled operations in presence of demand side management. The results in this paper showed that consumer participation who is responsible to price , not only lead to energy procurement cost decrement; but also load shifting from peak and expensive load hours to light and cheap ones and consequently energy cost reduction, causes cost decrement for the other clients . In this text , different scenarios were discussed consist of network islanding with and without DR . consumer bidding Definition for different load preferences caused a new method of DSM introduction in this text. Load preferences can be defined with any number and price. Although Modeling methods of different load preferences for different kinds of consumers can be several . Load participation increment caused critical load outage decrement and energy average cost increment.In general , Demand response causes market efficiency and operational security increment. If it execute DR correctly ,it limits lack of energy in power market and improves operational security with redundancy variable generation. Demand response programs design depends on market condition at a specific zone .it is concluded that operation with attention to DR objective function with smoothen is much more effective than DR objective function.

References

[1] A. Aslani, M. Naaranoja ,E. Antila , M. Golbaba,"Identification of the Situation of Renewable Energy Alternatives in the Criteria known by private sector investors (Case study: Iran)", International Journal of Renewable Energy Research (IJRER). 2012 May 12;2(2):332-7.

[2] S. Reza, T. Nitol, I. Abd-Al-Fattah,"Present scenario of renewable energy in Bangladesh and a proposed hybrid system to minimize power crisis in remote areas", International Journal of Renewable Energy Research (IJRER). 2012 May 12;2(2):280-8.

[3] A. Dhass, H. Santhanam. “Cost effective hybrid energy system employing solar-wind-biomass resources for rural electrification”, International Journal of Renewable Energy Research (IJRER). 2013 Mar 19;3(1):222-9.

[4] M. Islam, S. Gupta, N. Raju, M. Masum, S. Karim. “Potentiality of small-scale hydro power plant using the kinetic energy of flowing water of Gumoti&Surma river of Bangladesh: an energy odyssey”. International Journal of Renewable Energy Research (IJRER). 2013 Mar 19;3(1):172-9.

[5] C. Zhao, J. Wang, J. P. Watson and Y. Guan, "Multi-Stage Robust Unit Commitment Considering Wind and Demand Response Uncertainties," in IEEE Transactions on Power Systems, vol. 28, no. 3, pp. 2708-2717, Aug. 2013.

[6] M. Muratori and G. Rizzoni, "Residential Demand Response: Dynamic Energy Management and Time-Varying Electricity Pricing," in IEEE Transactions on Power Systems, vol. 31, no. 2, pp. 1108-1117, March 2016.

[7] S. Li, D. Zhang, A. B. Roget and Z. O'Neill, "Integrating Home Energy Simulation and Dynamic Electricity Price for Demand Response Study," in IEEE Transactions on Smart Grid, vol. 5, no. 2, pp. 779-788, March 2014.

[8] C. De Jonghe, B. F. Hobbs and R. Belmans, "Optimal Generation Mix With Short-Term Demand Response and Wind Penetration," in IEEE Transactions on Power Systems, vol. 27, no. 2, pp. 830-839, May 2012.

[9] N. H. Tran, C. T. Do, S. Ren, Z. Han and C. S. Hong, "Incentive Mechanisms for Economic and Emergency Demand Responses of Colocation Datacenters," in IEEE Journal on Selected Areas in Communications, vol. 33, no. 12, pp. 2892-2905, Dec. 2015.

[10] A. Safdarian, M. Fotuhi-Firuzabad and M. Lehtonen, "A Distributed Algorithm for Managing Residential Demand Response in Smart Grids," in IEEE Transactions on Industrial Informatics, vol. 10, no. 4, pp. 2385-2393, Nov. 2014.

[11] D. T. Nguyen, M. Negnevitsky and M. de Groot, "Pool-Based Demand Response Exchange—Concept and Modeling," in IEEE Transactions on Power Systems, vol. 26, no. 3, pp. 1677-1685, Aug. 2011.

[12] H. Huang, F. Li and Y. Mishra, "Modeling Dynamic Demand Response Using Monte Carlo Simulation and Interval Mathematics for Boundary Estimation," in IEEE Transactions on Smart Grid, vol. 6, no. 6, pp. 2704-2713, Nov. 2015.

[13] K. Samarakoon, J. Ekanayake and N. Jenkins, "Reporting Available Demand Response," in IEEE Transactions on Smart Grid, vol. 4, no. 4, pp. 1842-1851, Dec. 2013.

[14] O. Ma, "Demand Response for Ancillary Services," in IEEE Transactions on Smart Grid, vol. 4, no. 4, pp. 1988-1995, Dec. 2013.

[15] Y. Wang, I. R. Pordanjani and W. Xu, "An Event-Driven Demand Response Scheme for Power System Security Enhancement," in IEEE Transactions on Smart Grid, vol. 2, no. 1, pp. 23-29, March 2011.

[16] D. T. Nguyen, M. Negnevitsky and M. de Groot, "Market-Based Demand Response Scheduling in a Deregulated Environment," in IEEE Transactions on Smart Grid, vol. 4, no. 4, pp. 1948-1956, Dec. 2013.

[17] K. Ma, G. Hu and C. J. Spanos, "A Cooperative Demand Response Scheme Using Punishment Mechanism and Application to Industrial Refrigerated Warehouses," in IEEE Transactions on Industrial Informatics, vol. 11, no. 6, pp. 1520-1531, Dec. 2015.

[18] F. Y. Xu and L. L. Lai, "Novel Active Time-Based Demand Response for Industrial Consumers in Smart Grid," in IEEE Transactions on Industrial Informatics, vol. 11, no. 6, pp. 1564-1573, Dec. 2015.

[19] P. Faria, Z. Vale, J. Soares and J. Ferreira, "Demand Response Management in Power Systems Using Particle Swarm Optimization," in IEEE Intelligent Systems, vol. 28, no. 4, pp. 43-51, July-Aug. 2013.

[20] E. Nekouei, T. Alpcan and D. Chattopadhyay, "Game-Theoretic Frameworks for Demand Response in Electricity Markets," in IEEE Transactions on Smart Grid, vol. 6, no. 2, pp. 748-758, March 2015.

[21] S. Papathanassiou, N. Hatziargyriou, K. Strunz, “A benchmark low voltage microgrid network”. In Proceedings of the CIGRE symposium: power systems with dispersed generation, Apr 13 (pp. 1-8). 2005.

10. Appendix

The properties of different scenarios under consideration is shown in table 3, as follow:

Table 3. Different scenarios under study

<table>
<tr><td colspan="3">description</td><td>abbreviation</td><td>scenario</td></tr>
<tr><td colspan="3">Connected to upstream without demand response</td><td>SCE1</td><td>Scenario 1</td></tr>
<tr><td colspan="3">Critical and normal part of loads</td><td rowspan="2">programs</td><td rowspan="2">Scenario3
Considering</td></tr>
<tr><td>DOMESTIC</td><td>INDUSTRIAL</td><td>COMMERCIAL</td></tr>
</table>

α	1- α	α	1- α	α	1- α		demand response
0.05	0.95	0.02	0.98	0.05	0.95	SCE3DR1	
0.1	0.9	0.04	0.96	0.1	0.9	SCE3DR2	
0.15	0.85	0.06	0.94	0.15	0.85	SCE3DR3	
0.2	0.8	0.08	0.92	0.2	0.8	SCE3DR4	
0.25	0.75	0.1	0.9	0.25	0.75	SCE3DR5	
0.3	0.7	0.12	0.88	0.3	0.7	SCE3DR6	