Mansoura University
Faculty of Engineering
Mansoura Engineering Journal

A Novel Algorithm for Day-Ahead Real Time Pricing for Energy Management in Smart Grid
خوارزمية جديدة للتسعير لإدارة الطاقة في الشبكات الذاتية

Islam M. Ismael, *Mohammed Saeed, Sahar S. Kaddah* and Sobhy M. Abdelkader

KEYWORDS:
Energy Systems, Demand Side Management, Renewable Energy Sources.

الملخص العربي:-إن الهدف الرئيسي لإدارة الطاقة هو إنتاج الطاقة المطلوبة بأقل تكلفة وأقل تأثير بيئي. يقدم هذا البحث خوارزمية جديدة لإعادة تشكيل منحنى الحمل من خلال التسعير اليومى لكل ساعة. يتم تحديد الجدول الزمني للساعة القادمة مسبقا بطريقة تشجع العملاء على تعديل أكبر قدر ممكن من خصائص استهلاكهم وفقا لتوافر مصادر الطاقة المتجددة. وتتكون التقنية المقترحة من ثلاث خطوات معقدة استنادا لبرمجة غير خطية باستخدام خوارزمية البرمجة المتسلسلة الديناميكية . الأولى هى تحديد نمط الاستهلاك الأمثل لكل نوع حمل والذي يحسن الاستفادة من مصادر الطاقة التقليدية من خلال تقليل نسبة الذروة إلى المتوسط. والثانية هى تحديد إشارة السعر الأمثل والتى تزيد من توفير العملاء بعد اتباع هذا النمط الاستهلاك الأمثل والمحدد من الخطوة الأولى. أما الخطوة الأخيرة فهى اختبار العملاء للحد الأدنى من تكلفة الاستهلاك. ويتم التحقق من أداء الخوارزمية المقترحة من خلال تطبيقها على نموذج لشبكة ذكية ذات جهد منخفض تشتمل على مختلف الأحمال السكنية والتجارية والصناعية. وأثبتت نتائج المحاكاة فعالية التقنية المقترحة الجديدة لتحقيق الإدارة المثلى للطاقة

***Abstract*—The main objective of Energy Management is to produce demanded power with least cost and least environmental effect. This paper presents a novel algorithm for reshaping the load demand profile via day ahead hourly pricing. The day ahead hourly price schedule is determined in such a way that encourages customers to modify as much as possible of their consumption profile according to renewable energy availability. The proposed technique is composed of three optimization problems based on Non Linear Programming (NLP) solver using Sequential Dynamic Programming (SDP) algorithm. The first one is to determine the optimal consumption pattern for each load type that improves the utilization of the conventional generation through minimizing its peak to average ratio (PAR). The second is to determine the optimal price signal, which maximizes customer saving after following that optimal consumption pattern. The last one is the customer test for minimum consumption cost. The Performance of the proposed algorithm is verified by applying it to a low voltage benchmark of a smart grid with residential, commercial, and industrial loads. The simulation results proved the effectiveness of the new proposed technique for achieving optimal energy management**

I. INTRODUCTION

NOWADAYS, smart grid technologies enable customers to be active participants in the electricity market and help them to manage their consumption pattern in order to reduce their electricity bill[1].

An effective tool that can stimulate the demand side participation in the energy management process is the electricity pricing. The existing pricing schemes in electricity markets [2] are; flat pricing, Time of Use (TOU) pricing, Real Time Pricing (RTP), and Day-Ahead Real Time Pricing (DA-RTP). The flat pricing has been used in traditional energy systems, in which the prices are fixed within a season and the only way to reduce the electricity bills is to consume less electricity. In the TOU pricing scheme, the daily load is divided

Received: (11 July, 2017) - accepted: (15 August, 2017)
Islam M. Ismael, Dept. of Electrical Engineering, Faculty of Engineering, Mansoura University, Egypt (e-mail: islamm.ismael@gmail.com)
Mohammed Saeed, Dept. of Electrical Engineering, Faculty of Engineering, Mansoura University, Egypt (e-mail:m.saed@mans.edu.eg)
Sahar S. Kaddah, Professor of Electrical Engineering, Dept. of Electrical Engineering, Faculty of Engineering, Mansoura University, Egypt (e-mail: skaddah@mans.edu.eg)
Sobhy M. Abdelkader, Professor of Electrical Engineering Dept. of Electrical Engineering, Faculty of Engineering, Mansoura University, Egypt, E-mail: sakader@mans.edu.eg.-sobhy_abdelkader@yahoo.com

to peak load, medium, and off-peak load; and the price is kept fixed within each category. The third pricing scheme is the RTP in which the provider announces the real time prices; this scheme requires continuous real time communication between the energy provider and the customers, which is not attractive from the user perspective [3]. Demand Response based on RTP and DA-RTP may be centralized or decentralized. In the decentralized mode customers communicate with each other in a cooperative game to achieve a certain objective in order to receive low price signal depending on their contribution in achieving that objective. The centralized mode in which customers communicate directly to the power utility without interacting with each other and receive the price signal which is decided by the provider to achieve a certain objective [4]. Several works have tackled the problem of finding the real time price for energy management in smart grid [4-12]. In [4] two algorithms were developed for computing the optimal day-ahead prices based on consumer's willingness to shift their device usage, the first algorithm for computing the prices and the second for estimating user reaction to these prices. These two algorithms allowed the provider to dynamically adjust the offered prices based on user behavior. In [5] a day-ahead pricing model was proposed to maximize the provider's profit while consumer satisfaction was considered. A pricing framework has been proposed in [6], which is a time-dependent dynamic pricing strategy providing benefits for both the electric company and its customers while maximizing total social welfare. In [7] a day-ahead pricing model was proposed to maximize the operator's profit. The real time pricing proposed in [8] is based on a number of message exchanges between the customers and the provider to find the optimal energy consumption level for each customer. The pricing algorithm introduced in [9] is an incentive-based scheme to find the optimal energy consumption for each user for minimizing the energy cost in the system using game-theory analysis. A real time pricing has been presented in [10] based on Stackelberg game to capture the interactions between customers and provider for achieving optimal load control of devices by forming a virtual electricity-trading process. In this process, the provider (leader) is offering virtual prices, and the customers (followers) were supposed to purchase energy, and optimization problems are formed for each player to help in selecting the optimal strategy, which is proved through simulation results to be effective at achieving the optimal load control of devices in response to RTP changes. A stochastic mixed-integer linear programming optimization model was proposed in [11] to determine the optimal bidding strategy in the day-ahead market by minimizing the expected net cost of the smart grid. A real-time pricing algorithm for managing the interactions among the customers and the energy provider, and finding the optimal energy consumption for each customer to maximize their welfare has been presented in [12]. This paper presents a centralized DA-RTP algorithm to manage the consumption pattern of customers in order to reduce the stress on the grid and reduce the generation cost by minimizing the PAR of the generated power from the conventional generators, which is characterized by a high operating cost. The main contributions of the paper are: developing a new pricing algorithm; introducing a framework for Energy Management System (EMS) considering demand side management; and formulating a multi-objective optimization problem from three optimization problems, the first one ensures that the PAR of the nonrenewable generators is minimized; the second one ensures maximization of customer saving after shifting; and the last one ensures that the optimal consumption pattern decided by the operator is the best consumption pattern from the customer point of view for minimum consumption cost. The following two subsections present short introduction and brief backgrounds to energy management and demand response.

A. *Energy Management in Smart Grid*

Energy Management is a crucial activity in the operation of the smart grid. The main objective of Energy Management is to produce demanded power with least cost and least environmental effect. The Energy Management task can be divided into two sub-tasks, Generation Energy Management and Load Energy Management. Generation energy management is to plan a generation schedule for each unit in each hour on the next day to minimize the fuel cost, minimize the harmful gas emissions, and maximize the use of renewable energy resources. While load energy management is to plan the demand for each hour on the next day, based on the price signal, to match the cheapest supply to minimize the electricity cost. Load management can be done by shifting the load of customers reacting to the price signal and move their consumption from hours with high price to hours when the price is more beneficial. Current practice and research on energy management in the smart grid focus mainly on one of the following objectives; emission control, maximizing grid profit, minimizing cost, maximizing energy efficiency, or reshaping demand profile. This paper is focused on the objective of reshaping demand profile so as to flatten the net load on conventional generation. The PAR is introduced in this work as a measure of the flatness of load on the conventional generation. The proposed technique aims at minimizing the PAR to ensure better operation as well as generation cost of the conventional generators. The proposed energy management system uses the forecasted consumption, forecasted renewable generation, and a set of defined management objectives to determine the optimal prices for each load type, new demand profile for each load type, and optimal generation of each Distributed Energy Resource (DER) as shown in figure 1.

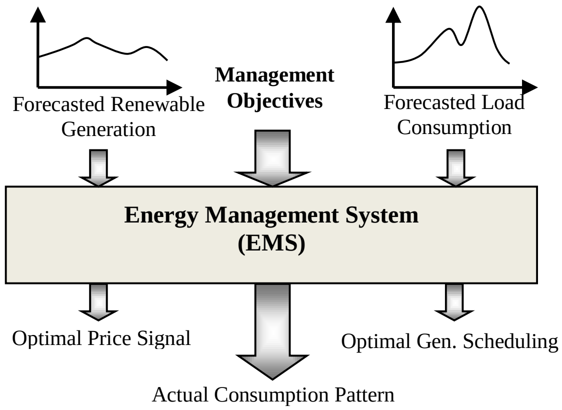


Figure 1. Energy Management System

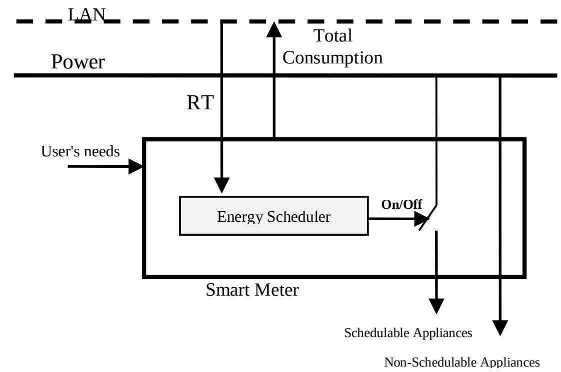


Figure 2. Operation of the Smart Meter for Performing Demand Response

B. Demand Response

According to the U.S. Department of energy, Demand Response (DR) is defined as "*changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time to minimize the electricity cost*" [13]. Demand response is considered as the most effective solution for smoothing the demand and hence reducing the system stress. DR helps the customer to modify their demand in order to follow the available supply, especially in regions with high penetration of renewable energy resources. Among the benefits that DR can offer are saving the customer's money, reducing stress on the grid at certain hours, reducing the overall operation cost, increasing the utilization of renewable generation, decreasing the Co_2 emissions, and lowering the probability of blackouts. The most common demand side management techniques are peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape [14]. Load shifting is widely applied as the most effective load management technique in current distribution network. An important economical term when discussing DR is the elasticity, which describes the customer's response to price change. Elasticity describes the willingness to shift load from peak hours to off-peak hours in response to price changes, without changing the total consumption. In a smart grid environment, the main part of the energy management system is the smart end-use devices with smart meter. The smart meter is associated with an energy scheduling device for automatically responding to the price variations in order to minimize the peak load and optimize the user's total energy cost as shown in figure 2 [15]. This helps the customers to reduce their electricity costs by consuming the electricity in times of the day when the overall consumption is low. As seen in figure 2, the task of the energy scheduler in the smart meter is to determine the optimal choice of the energy consumption for each appliance.

The remaining of this paper is organized as follows: Section 2 presents a framework for energy management in smart grid. Section 3 describes the proposed pricing algorithm. In section 4, the tested benchmark for the smart grid system is described and also the simulation results for three different consumption patterns for residential, commercial, and industrial loads are discussed. Finally the paper is concluded in section 5.

II. Framework of Energy management in the smart grid

The smart grid operator coordinates the grid operation by interacting between the supply and the load. It collects data from the customers about their needs and supply them with the suitable price signal which satisfies their needs and reduces the stress on the smart grid as shown in figure 3 and can be explained as follow;

1. The operator collects data about the forecasted renewable generation, the forecasted demand of each customer, the percentage of customers, which will participate in DR and the maximum allowable load to be shifted. These data is used to determine the optimal pricing for each load type.
2. The operator sends a message to each customer contains the optimal price signal for each hour of the next day and the permissible power at each hour for these prices, and the percentage of increase in price for the excess consumption.
3. The customer receives this message and decides the actual consumption based on this price signal for minimum consumption cost and sends a message contains the actual consumption pattern to the operator.
4. The operator receives back the actual consumption data from each customer and sends a message contains the total actual demand to the supply side for optimal operation of each DER.
5. The supply side receives back the total actual demand to determine the optimal scheduling and sends a message to the operator contains the generation cost at each hour of the next day.

III. The Proposed Pricing Algorithm

The objective of the proposed algorithm is to determine the optimal DA-RTP signal for each load type that impels the customers to change their consumption in order to reduce the total generation cost. The proposed algorithm is implemented in four steps, which can be described in the flowchart shown in figure 4. The proposed DA-RTP algorithm is divided into four main steps as follows:-

Step (1): Determining the Optimal Consumption Pattern of each Load Type

The forecasted consumption for each group of load type i at time interval t can be divided into controlled (Group A) and uncontrolled (Type B) as;

$$P_{i,t}^{for_A} = \alpha_i P_{i,t}^{for} \tag{1.a}$$

$$P_{i,t}^{for_B} = (1 - \alpha_i) \tag{1.b}$$

The optimal consumption pattern of group A for each load type is obtained by reshaping the forecasted consumption of this group through shifting load blocks within the maximum allowable shifting without changing the total daily consumption of this group. The objective of this shifting is to both maximize the utilization of the available renewable generation and also to improve the duty cycle of the conventional generation by making its output as level as possible. This objective is achieved by solving the following optimization problem.

Objective function:

$$min\left(\frac{P_{max}^{NRen}}{P_{avg}^{NRen}}\right) \tag{2}$$

$$P_t^{NRen} = -P_t^{Ren} + \sum_{i=1}^{N}\left(P_{i,t}^{opt_A} + P_{i,t}^{for_B}\right) \tag{3}$$

Subjected to the following constraints:

$$\sum_{t=1}^{24} P_{i,t}^{opt_A} = \sum_{t=1}^{24} P_{i,t}^{for_A} \tag{4}$$

$$(1 - \beta_i)P_{i,t}^{for_A} \le P_{i,t}^{opt_A} \le (1 + \beta_i)P_{i,t}^{for_A} \tag{5}$$

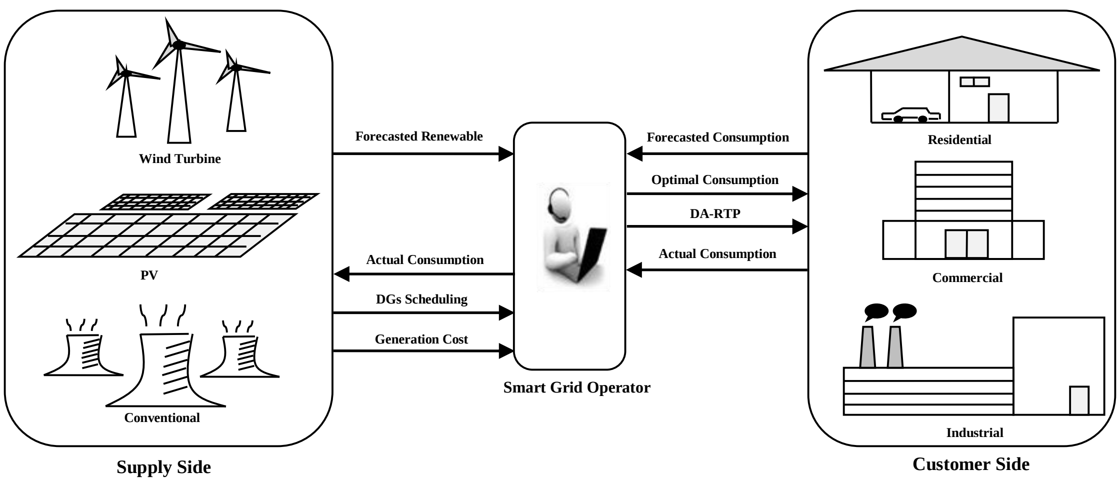


Figure 3. Information Exchange between the Operator, Customer, and Supply

Step (2): Determining the New Price Signal for each Load Type

Having the optimal consumption pattern determined in step 1, the operator determines the new price signals for the day ahead, which motivates the customers to modify their consumption to follow the optimal pattern. The new price is determined in a way to maximize the savings to customers following the optimal pattern; hence encouraging the customers to shift parts of their consumption to benefit from these saving opportunities. The maximum possible saving is gained when the shifted power is the same as the difference between the forecasted and optimal pattern.

This shifted power is determined as:

$$P_{i,t}^{sh_A} = P_{i,t}^{for_A} - P_{i,t}^{opt_A} \tag{6}$$

The new price signals are obtained by solving the following optimization problem.

Objective function

$$Max\left(\sum_{t=1}^{24} \rho_{i,t}^{New} * P_{i,t}^{sh_A}\right) \tag{7}$$

Subjected to the following constraints:

$$\rho_{i,t}^{New} = \rho_{i,t}^{Old} + \Delta\rho_{i,t} \tag{8.a}$$

$$\Delta\rho_{i,t} = \varepsilon_i P_{i,t}^{sh} \tag{8.b}$$

$$(1 - \gamma_i)\rho_{i,t}^{Old} \le \rho_{i,t}^{New} \le (1 + \gamma_i)\rho_{i,t}^{Old} \tag{9}$$

To avoid an excessive shifting of consumption to the periods of low price, the obtained price signal from this optimization is only for the consumption up to the optimal value, and any increase in consumption above the optimal will be faced by an increase in price through a penalty factor, this can be described as;

$$cost_{i,t} = \begin{cases} \rho_{i,t}^{New} P_{i,t}^{act_A} & P_{i,t}^{act_A} \le P_{i,t}^{opt_A} \\ \rho_{i,t}^{New}\left(P_{i,t}^{opt_A} + (1 + \delta_i)\left(P_{i,t}^{act_A} - P_{i,t}^{opt_A}\right)\right) & P_{i,t}^{act_A} \ge P_{i,t}^{opt_A} \end{cases} \tag{10}$$

Step (3) Implementing the New Price Signal

In this step, the new DA-RTP price signal is implemented with the actual consumption pattern for each load type with the objective of minimizing the total cost. It is to be mentioned that the first step determines the load shifts that improves the utilization of renewable energy sources and enhances the operation of the conventional generators, whereas the optimization problem of this step aims at minimizing the costs to customers. The problem of minimizing the cost to customers through shifting the load based on actual load data is formulated as follows.

Objective function:

$$min \sum_{t=1}^{24} \begin{matrix} \rho_{i,t}^{New} P_{i,t}^{act_A} u\left(P_{i,t}^{opt_A} - P_{i,t}^{act_A}\right) + \\ \rho_{i,t}^{New}\left(P_{i,t}^{opt_A} + (1+\delta_i)\left(P_{i,t}^{act_A} - P_{i,t}^{opt_A}\right)\right) u\left(P_{i,t}^{act_A} - P_{i,t}^{opt_A}\right) \end{matrix} \quad (11)$$

Subjected to the following constraints:

$$\sum_{t=1}^{24} P_{i,t}^{act_A} = \sum_{t=1}^{24} P_{i,t}^{for_A} \quad (12)$$

$$(1-\beta_i) P_{i,t}^{for_A} \leq P_{i,t}^{act_A} \leq (1+\beta_i) P_{i,t}^{for_A} \quad (13)$$

Step (4) Determining the Customer Saving after Shifting.

The final step is to test the proposed algorithm through determining the savings to customers interacting with the DA-RTP scheme. The saving gained by the customers, in group A of load type *i*, by shifting their consumption can be determined as follows;

$$Cost_i^{for_A} = \sum_{t=1}^{24} \begin{matrix} \rho_{i,t}^{New} P_{i,t}^{for_A} u\left(P_{i,t}^{opt_A} - P_{i,t}^{for_A}\right) + \\ \rho_{i,t}^{New}\left(P_{i,t}^{opt_A} + (1+\delta_i)\left(P_{i,t}^{for_A} - P_{i,t}^{opt_A}\right)\right) u\left(P_{i,t}^{for_A} - P_{i,t}^{opt_A}\right) \end{matrix} \quad (14)$$

$$Cost_i^{act_A} = \sum_{t=1}^{24} \begin{matrix} \rho_{i,t}^{New} P_{i,t}^{act_A} u\left(P_{i,t}^{opt_A} - P_{i,t}^{act_A}\right) + \\ \rho_{i,t}^{New}\left(P_{i,t}^{opt_A} + (1+\delta_i)\left(P_{i,t}^{act_A} - P_{i,t}^{opt_A}\right)\right) u\left(P_{i,t}^{act_A} - P_{i,t}^{opt_A}\right) \end{matrix} \quad (15)$$

$$\%Saving_i^A = \frac{Cost_i^{for_A} - Cost_i^{act_A}}{Cost_i^{for_A}} \quad (16)$$

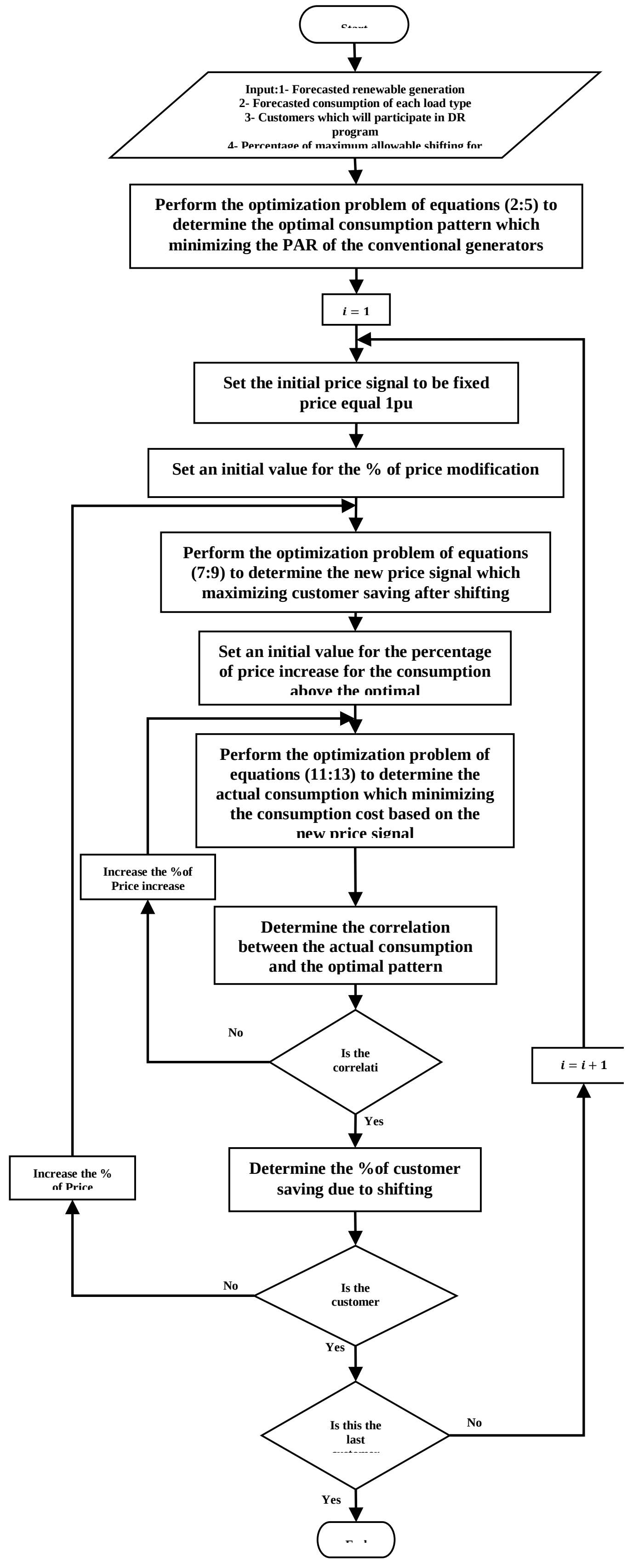


Figure 4. Flowchart for the Pricing Algorithm

IV. APPLICATION AND TEST RESULTS

The proposed algorithm was tested on a typical smart microgrid 14-bus low voltage distribution test network [16]. This test system is shown in figure 5.

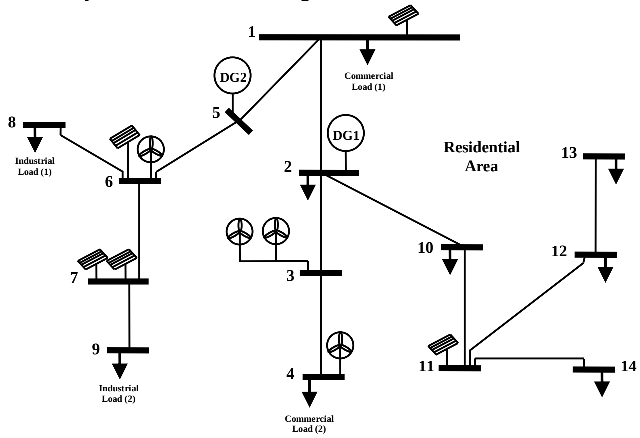


Figure 5. Typical Smart Microgrid Test Network

Three types of customers are considered in the smart microgrid: one hundred of residential customers, two commercial and two medium industrial customers. Figure 6 shows the forecasted data for both load and renewable generation. The aggregated daily load curves for the three load types are shown in figure 6 [17].

A variety of distributed energy resources, such as two micro turbine, four windturbines, and five photovoltic arrays are installed in the grid. It is assumed that all DGs produce active power at a unity power factor. The four wind turbine are of the same type: 25 kW power rated each, and the five PV arrays are of the same type of 20 kW each. The forecasted renewable generation are shown in figure 7.

Dynamic programming is originally conceived as a method to solve dynamic optimization models over time. A Matlab code is built based on Sequential Dynamic Programming (SDP) technique composed of three complex subroutines for the three main optimization problems.

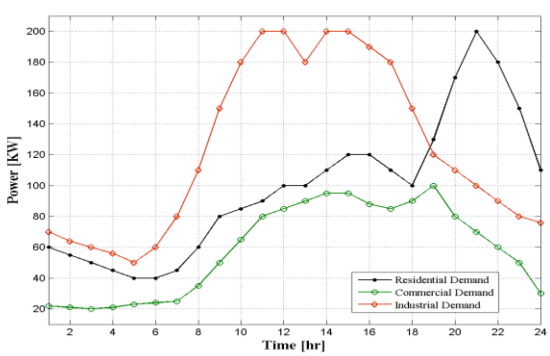


Figure 6 The forecasted Consumption for the Three Load Types

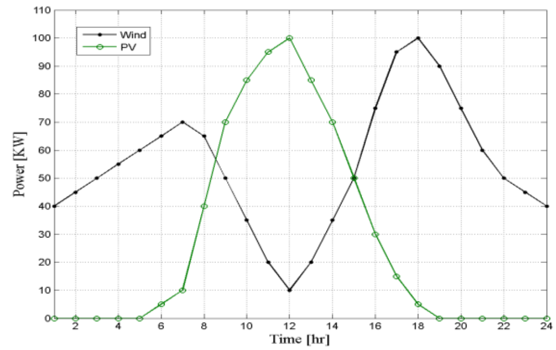


Figure 7 The forecasted Renewable Generation

The optimal consumption pattern for each load type, obtained by minimizing the PAR of the conventional generation is determined and shown in figure 8. The operator decides to increase or decrease the consumption of each load type at each time interval so as to reduce the difference between the maximum and minimum values of the non-renewable generation. The percentage of increasing or decreasing in the consumption at any period mustn't be greater than 20% of the forecasted consumption at that period, and the total energy consumed by any load is unchanged after energy management.

The modifications to the forecasted consumption pattern, demand shifts, required for different loads to follow the corresponding optimal pattern are shown in figure 9.

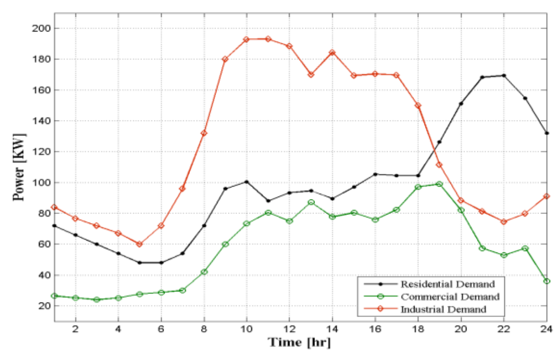


Figure 8 The Optimal Consumption for the Three Load Types

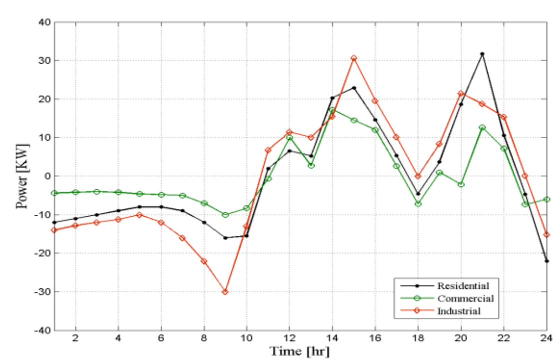


Figure 9 The Required Power to be Shifted

As it is clear in figure 9, there are times with high positive load shifts and others with negative shifts. This suggests that increasing the price at time intervals with high positive shifting will push the customers to reduce their consumption at these periods and move it to times with negative shift and lower prices. The relationship between this price adjustment and the customer saving is shown in figure 10.

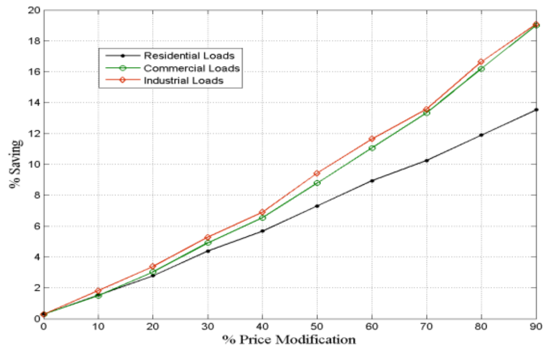
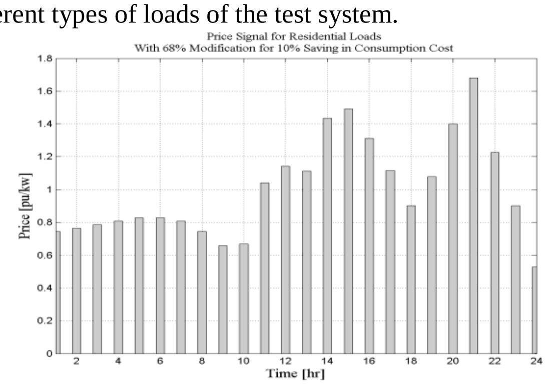


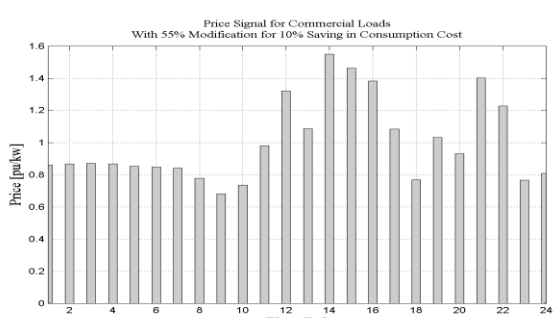
Figure (10) %age Saving Variation with the percentage Price Modification

It can be noticed that the customer saving depends on the limits of allowable price change of the DA-RTP; the wider the price change band the more saving the customer can gain. However, the customers may get tempted by the increased saving and shift larger blocks of their loads. This may lead to shift the peak load to the time of low price and hence the problem of load profile improvement remains unsolved.

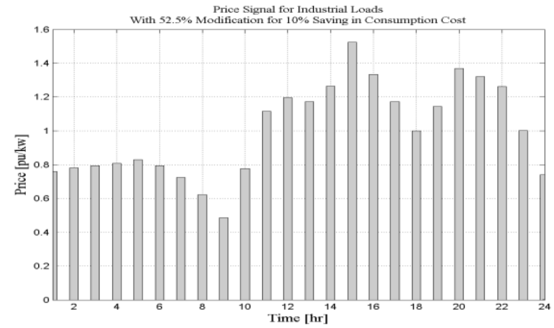
To prevent such a situation a further price adjustment may be required. One way to do it, adding an extra cost per unit consumed above the optimal value. These price signals calculated to insure 10% savings for customers participating in the demand response program are shown in figure 11 for different types of loads of the test system.



(a) DA-RTP for Residential Loads



(b) DA-RTP for Commercial Loads



(c) DA-RTP for Industrial Loads

Figure 11. DA-RTP Signal for the Consumption Up To the Optimal

The total system consumption and both renewable and conventional generation are shown in figure 12 for the case of not implementing the proposed DA-RTP scheme. As it can be noticed from the figure, the maximum and minimum values of output power from conventional generators are 315 kW and 53 kW at t=15 and t=5 respectively. The PAR of the generated power is 1.60, which is a high ratio that may cause high stress on the grid and sure will result in high generation cost.

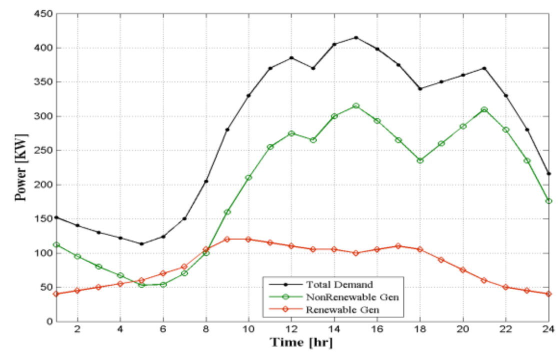


Figure 12. Total Consumption, Renewable, and Conventional Generation without the proposed algorithm

Applying the proposed algorithm, the maximum value of the conventional generation is reduced to 247kW and its minimum value is increased to 75.6 kW as shown in figure 13. The PAR is reduced to 1.25 with a reduction of 21.8 %, which reduces the generation cost and help relief the stress on the grid. It can also be noticed that the total consumption tracks well the renewable generation, which means efficient utilization of renewable energy. Also the maximum value of the total consumption is reduced to 367 kW and moves to the same time of the maximum renewable generation.

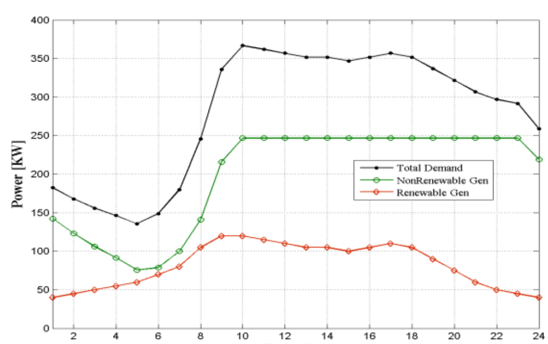


Figure 13. Total Consumption, Renewable, and Conventional Generation with the proposed algorithm

V. CONCLUSION

In this paper a novel day-ahead real-time pricing algorithm for energy management in smart grid is presented. The energy management is achieved by changing the consumption pattern of each load type in order to reduce the PAR of the non-renewable generation for minimum generation cost. The load consumption pattern is modified by setting a price signal for each load type to encourage them to shift their loads to the off-peak periods, and to optimally track the renewable generation by flatting the power of the non-renewable generation. The proposed model has been applied to a typical smart microgrid with three different load types. The novel proposed algorithm proved its flexibility and robustness to any changes in the system. By applying the proposed algorithm, the total generation cost, the stress on the grid, and the customer's bill can be reduced.

Here is the list of symbols and its description which is used in this paper;

Symbol	Description
$P_{i,t}^{for}$	The forecasted consumption for load type i at time interval t
α_i	The percentage of group A for load type i which participates in DR program.
$P_{i,t}^{for_A}$	The forecasted consumption for group A of load type i at time interval t
$P_{i,t}^{for_B}$	The forecasted consumption for group B of load type i at time interval t
P_t^{Ren}	The renewable generation at time interval t
P_t^{NRen}	The non-renewable generation at time interval t
P_{max}^{NRen}	The maximum value of the non-renewable generation
P_{avg}^{NRen}	The average value of the non-renewable generation
PAR	The peak to average ratio of the non-renewable generation
$P_{i,t}^{opt_A}$	The optimal consumption for group A of load type i at time interval t
N	Total number of load types
β_i	The percentage of maximum allowable shifting for group A at load type i
$P_{i,t}^{sh_A}$	The required power to be shifted for group A of load type i at time interval t
$\rho_{i,t}^{Old}$	The original price at time interval t for load type i
$\rho_{i,t}^{New}$	The new price at time interval t for load type i
$\Delta\rho_{i,t}$	The change in price at time interval t for load type i
ε_i	The price conversion factor for load type i which converts the shifting power to a change in price
γ_i	The maximum percentage of price modification higher or lower than the original price for load type i
$P_{i,t}^{act_A}$	The actual consumption for group A of load type i at time interval t
δ_i	The percentage of price increase for load type i for the amount of consumption above the optimal
u	The unit step function, it is one for positive bracket and otherwise it is zero.

REFERENCES

[1] X. Fang, S.Misra, G. Xue, and D. Yang "Smart Grid – the New and Improved Power Grid: A Survey" IEEE Journal of Communication Surveys and Tutorials Vol. 14, 2012, PP: 944-980.

[2] A. Khan, A. Mohmood, A. Safdar, and Z. A. Khan "Load Forecasting, Dynamic Pricing, and DSM in Smart Grid: A Review" Elsevier, Renewable and Sustainable Energy Reviews Vol. 54, February 2016, PP 1311–1322.

[3] J. S. Vardakas, N. Zorba, and C. V. Verikoukis "A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms" IEEE Journal of Communication Surveys and Tutorials Vol. 17, 2015, PP: 152-178.

[4] C. Joe-Wong, S. Sen, S. Ha, and M. Chiange "Optimized Day-Ahead Pricing with Device-Specific Scheduling Flexibility" IEEE Journal on Selected Areas in Communications Vol. 30, 2012, PP: 1075-1085..

[5] M. Doostizadeh, and H. Ghasemi "A Day-Ahead Electricity Pricing Model Based on Smart Metering and Demand-Side Management" Elsevier, Energy Journal Vol. 46, October 2012, PP: 221–230.

[6] T. Chiu, Y. Shih, A. Pang, and C. Pai "Optimized Day-Ahead Pricing with Renewable Energy Demand-Side Management for Smart Grids" IEEE Internet of Things Journal 2016, Online ISSN: 2327-4662.

[7] M. Mazidi, H. Monsef, and P. Siano "Incorporating Price-Responsive Customers in Day-Ahead Scheduling of Smart Distribution Networks" Elsevier, Energy Conversion and Management Journal Vol. 115, 1 May 2016, PP:103–116.

[8] PedramSamadi, Amir-HamedMohsenian-Rad, Robert Schober, Vincent W.S. Wong, and JuriJatskevich "Optimal Real-time Pricing Algorithm Based on Utility Maximization for Smart Grid" Smart Grid Communications, 2010 First IEEE International Conference2010.

[9] Amir-HamedMohsenian-Rad, Vincent W. S. Wong, JuriJatskevich, Robert Schober, , and Alberto Leon-Garcia, "Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid" IEEE Transactions on smart grid,Vol.1, Dec. 2010, PP: 320-331.

[10] Mengmeng Yu and Seung Ho Hong "A Real-Time Demand-Response Algorithm for Smart Grids: A Stackelberg Game Approach" IEEE Transactions on smart grid, Vol. 7, March 2016, PP: 879-888.

[11] Guodong Liu, Yan Xu, and Kevin Tomsovic "Bidding Strategy for Microgrid in Day-Ahead Market Based on Hybrid Stochastic/Robust Optimization" IEEE Transactions on smart gridVol. 7, Jan 2016, PP: 227-237.

[12] Gh. Asadi, M. Gitizadeh, and A. Roosta "Welfare Maximization under Real-time Pricing in Smart Grid Using PSO Algorithm"Electrical Engineering (ICEE), 2013, 21st Iranian Conference,Publisher: IEEE.

[13] P. Siano "Demand Response and Smart Grids – A Survey" Elsevier, Renewable and Sustainable Energy Reviews Vol. 30, February 2014, PP: 461–478.

[14] T. Logenthiran, D. Srinivasan, and T. Shun "Demand Side Management in Smart Grid Using Heuristic Optimization" IEEE Transactions on Smart Grid,Vol. 3, Sept. 2012 PP: 1244 - 1252.

[15] L. Qian, Y. Jun, J. Huang, and Y. Wu "Demand Response Management via Real-Time Electricity Price Control in Smart Grids" IEEE Journal of Selected Areas in Communications,Volume: 31, July 2013, PP: 1268-1280.

[16] A. Zakariazadeh, S. Jadid, P. Siano "Smart microgrid energy and reserve scheduling with demand responseusing stochastic optimization" Elsevier, Electrical Power and energy Systems, Vol. 63, December 2014, Pages 523–533.

[17] W. Huang "Study on the operation of a Low-Voltage AC Microgrid with Multiple Distributed Generations" WSEAS Transactions on circuits and systems Vol. 9, December 2010 PP: 725-735.