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Research Paper on Home Energy Management System Using Genetic Algorithm

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Abstract: ***In the paper, an optimization method based on genetic algorithm was proposed. We propose a distributed framework for the demand response based on cost minimization. Each user in the system will find an optimal start time and operating mode for the appliances in response to the varying electricity prices by controlled and uncontrolled devices and different unit reading by different time scheduled by using GA based algorithm. In the proposed algorithm, each user requires only the knowledge of the price of the electricity, which depends on the aggregated load of other users, instead of the load profiles of individual users. In order for the users to coordinate with each other, we introduce a penalty term in the cost function, which penalizes large changes in the scheduling between successive iterations.***
Index Terms: Home energy management; real time pricing; genetic algorithm.

I. INTRODUCTION

In recent years, the public has been paying ever greater attention to problems associated with energy production and consumption. Energy-supply issues rightly constitute one of the most important issues that we face. In the absence of any viable alternative energy supply, a strategy that would result in energy savings is a legitimate goal. In this paper proposed algorithm, each user requires only the knowledge of the price of the electricity, which depends on the aggregated load of other users, instead of the load profiles of individual users. This paper presents an optimized home energy management system (OHEMS). The proposed scheme not only facilitates the integration of RES and ESS into the residential sector but also reduces the procurer's electricity bill as well as the PAR. In addition, the performance of the heuristic algorithms: genetic algorithm (GA). "Smart electricity system" has moved from conceptual to operational in the last few years. The smart grid has undergone significant innovation, with demand response, being one of the important focus areas. The principal goal of demand response is to reduce the generation cost of electricity by reducing the peak load and shifting peak hour demand to off-peak hours. Shifting electricity usage to off-peak hours is desired to allow for better utilization of the generated power, and reduce costs to both the consumers and utility companies. With the advent of advanced communication infrastructures that enable a reliable two-way communication between the energy provider and the end-users, it has become feasible for the utility company to provide the consumers with the time-dependent price of the electricity.

II. RELATED WORK

Recently, various DSM strategies have been proposed. Their common objectives are the minimization of electricity cost, reduction of PAR, curtailment of carbon emissions and improvement of power system efficiency. Some of the most recent related works solve the appliances scheduling problem as an optimization problem is as per the following.

Lee et al. [8], presents linear programming (LP) based residential energy management system (REMS) for minimization of electricity cost and PAR. Monotonic optimization based DSM strategy is proposed in [9], an optimal utilization technique for centralized RES has been demonstrated through mathematical modeling.

Z. Zhu et al. [10] proposes an integer linear programming (ILP) based appliances scheduling scheme to shift the controllable appliances from peak hours to off-peak hours. In [11], the optimization problem of household appliances is solved via mixed integer linear programming (MILP), different types of appliances are taken in problem formulation with the ultimate goal of electricity bill reduction.

In [12], a home automation system based on optimal stopping rule (OSR) is proposed. Simulation results shows, that OSR reduces the electricity bill with minimum appliances waiting time.

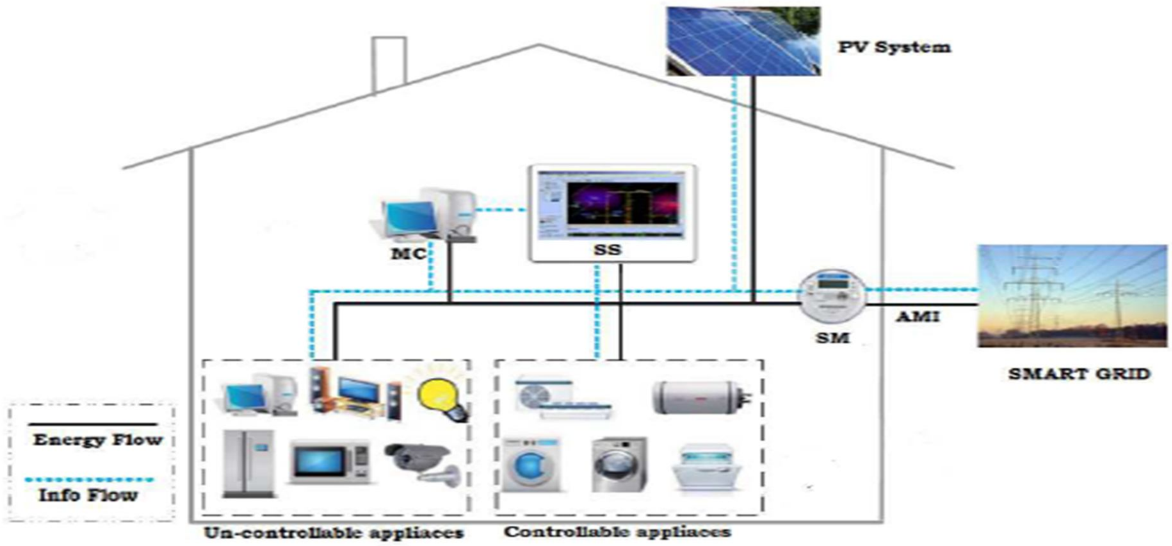
In [13], the authors demonstrate an efficient HEMS architecture for implementation of DSM in the residential sector. They combine RTP scheme with inclined block rate (IBR) because the use of only RTP signal may shift the peak demand from peak hours to off-peak hours. To eliminate the creation of new peak in the objective function is formulated and solved by using GA. Simulation results illustrate that proposed model is very effective for reduction of PAR and electricity cost.

In [14], the authors present a nature-inspired wind driven optimization (WDO) technique to solve multi-objective optimization problems. The WDO is a population-based iterative optimization technique. A population of small air parcels is randomly distributed in search space by assigning random
velocities and positions to each particle. In each iteration, the velocity and position of air parcels are updated when it moves toward the optimum pressure point. Simulation results show that WDO outperformed the classical and other heuristic optimization techniques.
In [15], the authors discuss that the time of use (ToU) pricing scheme and DR are the two strategies which motivate the consumers to reduce energy consumption during peak hours. A decision support program is demonstrated which forecast the energy demand and find an optimal time for appliance operation.
In [16], an evolutionary algorithm (EA) for the solution of cost minimization problem is proposed. Simulation results show that the proposed EA brings the user load curve near to the objective curve, where the objective curve and electricity price have an inverse relationship.
P. Yang et al. [17], presents a distributed algorithm (DA) for HEMS and grid optimization. In proposed DA the electricity price is used as an invisible hand to optimize the appliances scheduling and energy consumption.
Z. Weng et al. [18], demonstrates a fully automated EMS by using reinforcement learning (RL) techniques. The energy management and appliance scheduling problem are solved by observe, learn and adapt (OLA) algorithm which adds more intelligence to EMS.

III. PROPOSED SYSTEM ARCHITECTURE

In this paper, we propose a distributed energy scheduling algorithm as a demand response for the smart grid. We use day-ahead pricing scheme, where the price of the electricity for the day is determined on the previous day. We then find optimal operating times for the electric appliances and their corresponding energy consumptions by minimizing the overall cost of operation. Our approach is different from the related work in four main aspects: i) we jointly optimize both the start time and the energy consumption for each appliance of the user; ii) we bill all the users based on their time-dependent use of electricity; iii) we enforce realistic constraints on the operation of the appliances by categorizing them into two different classes; iv) we let the energy consumption vary in a discrete manner, which is more realistic. Further, our algorithm is fully distributed, where the only information available to the users is the prices for different time-periods.
Using this price, each user will find his energy consumption schedule. Since we allow the energy consumption to vary in a discrete fashion, the corresponding optimization problem will be NP-hard. Therefore, we employ a greedy iterative algorithm to find the sub-optimal energy consumption schedule of each user. In each iteration, all the users will communicate their energy consumption schedule to the utility company. The utility company will then adjust the price depending on the overall system load and broadcast the price to all the users. The users will then update their energy consumption based on the new price. These iterations continue until convergence.
We use numerical simulations to show that the proposed algorithm will result in lower cost for the consumers, higher profit for the utility companies, lower peak load, and lower load variance.

Controller Appliances	Un-controllable Appliances
Washing machine	Personal Computer
Air conditional	Security Cameras
Clothes Dryer	Microwave Oven
Water Heater	Refrigerator



A. GA Based Algorithm

GA is an iterative optimization algorithm inspired by the natural genetic process of the living organisms. Rather than working on a single solution, GA deals with different possible solutions in each iteration. GA begins its search with randomly initialized binary coded chromosomes. The chromosomes pattern of GA represents the ON/OFF state of appliances, and the length of chromosomes shows the number of appliances.

Length of chromosomes = L

Where, L is the number of household appliances.

Once the population (a set of solutions that shows the status of each appliance in a particular time slot) is created, fitness function of each possible solution is evaluated according to the objective function of the optimization problem. Here, the fitness of each population is evaluated using Equation. Then, a new population is created by applying the natural genetic operators: crossover and mutation. The GA parameters with their values on which it gives optimal results are listed in table.

Parameters	Value
Number of iteration	500
Population size	200
Pm	0.1
Pc	0.9
N	11

The working flow of GA is shown in Figure. In each iteration, a new population is produced through crossover and mutation. In the crossover step, two binary strings are crossover to create a new off spring. Crossover probability says how often crossover will be performed. If there is no crossover, offspring is exact copy of parents. If there is a crossover, offspring is made from parts of parents' chromosome. If crossover probability is 100%, then all offspring is made by crossover. If it is 0%, a whole new generation is made from exact copies of chromosomes from old population . Moreover, a larger crossover rate avoids premature convergence to the sub-optimal solutions, so, the best crossover rate selected for optimization problems is 90% as given by,

Pc = 0.9

To create randomness in the results so that the repetition of a population could be avoided we use mutation process. It changes one or more principles gene in a chromosome from its initial state. In natural genetic process, the probability of mutation is very low, so, an optimum mutation rate for optimization problems is,

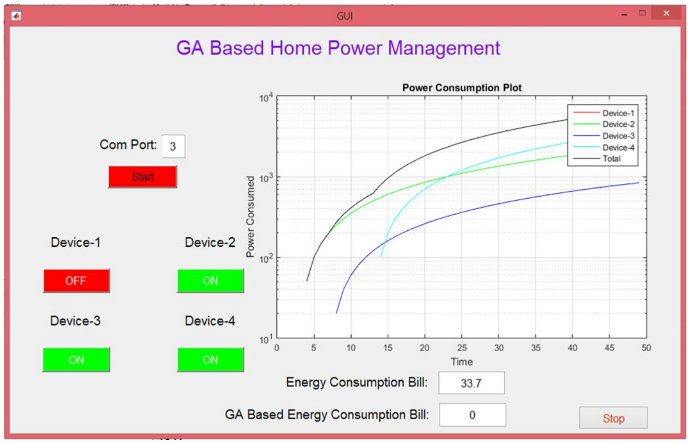
Pm = 1 - Pc

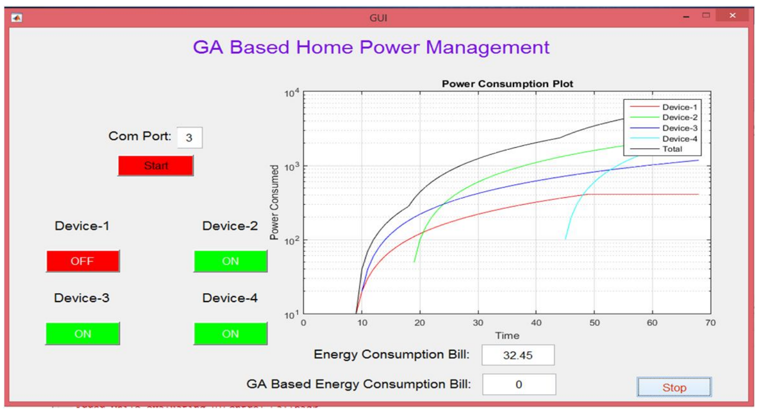
Once crossover and mutation are done, again a population is generated and fitness is evaluated and compared with previous population.

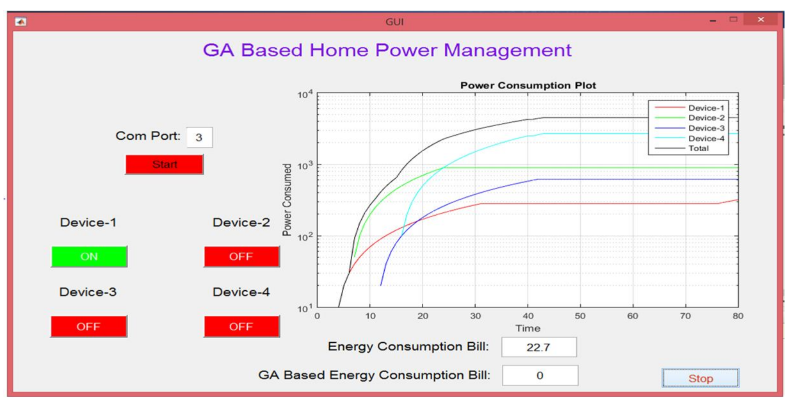
Fig: - GA Algorithm

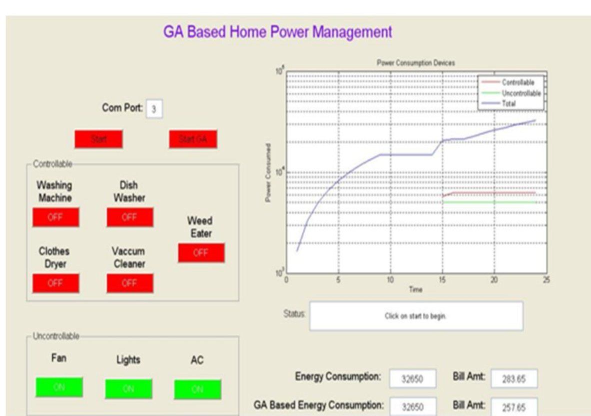
IV. SIMULATION RESULT

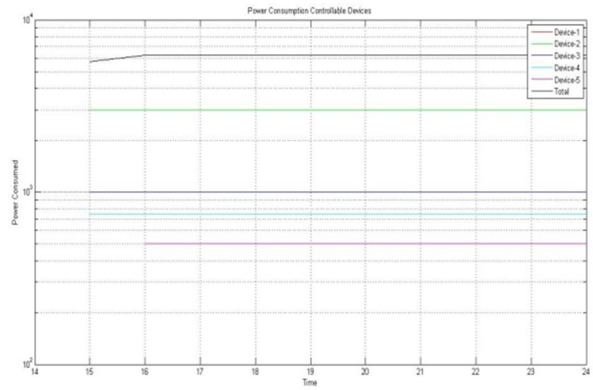
In this section, simulation results of the proposed OHEMS are presented. In the proposed scheme, the integration of RES and ESS, as well as the performance of algorithms GA is evaluated via two stages simulations. In the first case, the integration of RES and ESS into the residential sector are evaluated in terms of energy consumption pattern, and electricity bill as well as PAR reduction. While in the second case, the same performance metrics (energy consumption pattern, and electricity bill as well as PAR minimization) are used to evaluate the effectiveness of GA .

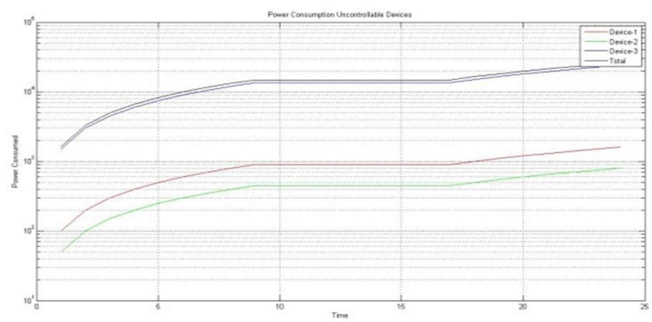

GUI
GA Based Home Power Management
Com Port: 3
Start
Device-1
OFF
Device-2
ON
Device-3
ON
Device-4
ON
Power Consumption Plot
Device-1
Device-2
Device-3
Device-4
Total
Power Consumed
Time
Energy Consumption Bill: 33.7
GA Based Energy Consumption Bill: 0
Stop


GUI
GA Based Home Power Management
Com Port: 3
Start
Device-1
OFF
Device-2
ON
Device-3
ON
Device-4
ON
Power Consumption Plot
Device-1
Device-2
Device-3
Device-4
Total
Power Consumed
Time
Energy Consumption Bill: 32.45
GA Based Energy Consumption Bill: 0
Stop


GUI
GA Based Home Power Management
Com Port: 3
Start
Device-1
ON
Device-2
OFF
Device-3
OFF
Device-4
OFF
Power Consumption Plot
Device-1
Device-2
Device-3
Device-4
Total
Power Consumed
Time
Energy Consumption Bill: 22.7
GA Based Energy Consumption Bill: 0
Stop


GA Based Home Power Management
Com Port: 3
Start
Start GA
Controllable
Washing Machine
Dish Washer
Weed Eater
Clothes Dryer
Vaccum Cleaner
Uncontrollable
Fan
Lights
AC
Power Consumption Devices
Controllable
Uncontrollable
Total
Power Consumed
Time
Status:
Click on start to begin.
Energy Consumption: 32650
Bill Amt: 283.65
GA Based Energy Consumption: 32650
Bill Amt: 257.65





V. CONCLUSION

In this paper, we proposed an RHEMS to facilitate the integration of RESs in the residential sector and to reduce the electricity bill as well as peak formation. First, the objective function is mathematically formulated and then evaluated by using GA-based scheduling in a dynamic pricing environment.

Simulations results show that the scheduling of household appliances and estimated renewable energy in response to dynamic pricing signal significantly reduce the electricity cost and PAR. Moreover, the proposed RHEMS achieve a favorable tradeoff between the user comfort and cost reduction. In future, we are interested in forecasting and integration of energy storage system in residential sector to increase the benefits from RESs.

REFERENCES

[1] Y. Guo, M. Pan, Y. Fang, Optimal Power Management of Residential Customers in the Smart Grid, IEEE Transactions on Parallel and Distributed Systems, vol. 23, no. 9, pp. 1593-1606, 2012.

[2] Alessandro, P. de Gianluca, D. Paolo, V. Antonio, Load Sceduling for Household Energy Consumption Optimization, IEEE Transaction on Smart Grid, pp. 2364-2373, vol. 4, no. 4, 2013.

[3] S. Shengan, P. Manisa, R. Saifur. Demand Response as a Load Shaping Tool in an Intelligent Grid With Electric Vehicles, IEEE Transactions on Smart Grid, pp. 624-631, vol.2, no.4, 2011.

[4] K. Maharjan, Demand Side Management: Load Management, Load Proling, Load Shifting, Residential and Industrial Consumer, Energy Audit, Reliability, Urban, Semi-Urban and Rural Setting. Saar-brcken, Germany: LAP (Lambert Acad. Publ.), 2010.

[5] T. Hubert, S. Grijalva. ”Realizing smart grid benefits requires energy optimization algorithms at residential level”. IEEE PES Innovative Smart Grid Technologies (ISGT), pp. 1-8, 2011.

[6] Tsui, Kai Man, and Shing-Chow Chan. ”Demand response optimizationfor smart home scheduling under real-time pricing.” Smart Grid, IEEE Transactions vol. 3, no. 4, pp. 1812-1821, 2012.

[7] Oberdieck, Richard, and Efstratios N. Pistikopoulos. ”Multi-objective optimization with convex quadratic cost functions: A multi-parametric programming approach.” Computers Chemical Engineering vol. 85, pp. 36-39, 2016.

[8] Lee, Jae Yong, and Seong Gon Choi. ”Linear programming based hourly peak load shaving method at home area.” IEEE 16th International Conference on Advanced Communication Technology (ICACT), 2014.

[9] Samadi, Pedram, et al. ”Optimal real-time pricing algorithm based on utility maximization for smart grid.” First IEEE International Conference on Smart Grid Communications (SmartGridComm), 2010.

[10] Z. Zhu, J. Tang, S. Lambotharan, W. H. Chin, Z. Fan, An integer linear programming based optimization for home demand-side management in smart grid, In Innovative Smart Grid Technologies (ISGT), IEEE PES, pp. 1-5, January 2012.

[11] Vardakas, John S., Nizar Zorba, and Christos V. Verikoukis. ”Power demand control scenarios for smart grid applications with finite number of appliances”, Applied Energy vol. 162, pp. 83-98, 2016.

[12] P. Yi, X. Dong, A. Iwayemi, C. Zhou, S. Li, ”Real-time opportunistic scheduling for residential demand response”, IEEE Transactions on Smart Grid, vol. 4, no. 1, pp. 227-34, 2013.

[13] Fernandes, Filipe, et al. ”Genetic algorithm methodology applied to intelligent house control.” IEEE Symposium on Computational Intelligence Applications In Smart Grid (CIASG), 2011.

[14] Bayraktar, Zikri, Muge Komurcu, and Douglas H. Werner. ”Wind Driven Optimization (WDO): A novel nature-inspired optimization algorithm and its application to electromagnetics.” Antennas and Propagation Society International Symposium (APSURSI), IEEE, 2010.

[15] Khomami, Hadis Pourasghar, and Mohammad Hossein Javidi. ”An= efficient home energy management system for automated residential demand response.” IEEE 13th International Conference on Environment and Electrical Engineering (EEEIC), 2013.

[16] Das, Swagatam, Ajith Abraham, and Amit Konar. ”Automatic clustering using an improved differential evolution algorithm”, IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans, vol. 38, no. 1, pp. 218-237, 2008.

[17] P. Yang, P. Chavali, E. Gilboa, A. Nehorai, Parallel Load Schedule Optimization with Renewable Distributed Generators in Smart Grids, IEEE Transactions on Smart Grid, vol. 4, no. 3, pp. 1431-1441, 2013.

[18] Wen, Zheng, Daniel O’Neill, and Hamid Maei. ”Optimal demand response using device-based reinforcement learning”, IEEE Transactions on Smart Grid, vol. 6, no. 5, pp. 2312-2324, 2013.

[19] Zhao, Zhuang, et al. ”An optimal power scheduling method for demand response in home energy management system”, IEEE Transactions on Smart Grid, vol. 3, no. 4, pp. 1391-1400, 2013.

[20] K. Deb, ”Multi-objective optimization using evolutionary algorithms”, John Wiley and Sons, 2001.

