engineering proceedings

Proceeding Paper

Demand Side Management and Dynamic Economic Dispatch Using Genetic Algorithms †

Khaled Dassa and Abdelmadjid Recioui *

Laboratory of Signals and Systems, Institute of Electrical and Electronic Engineering, University M'hamed Bougara of Boumerdes, Boulevard de L'indépendance, Boumerdes 35000, Algeria; k.dassa@univ-boumerdes.dz
* Correspondence: a_recioui@univ-boumerdes.dz

† Presented at the 1st International Conference on Computational Engineering and Intelligent Systems, Online, 10–12 December 2021.

Abstract: The purpose of this work is to find the optimal energy management mix in order to maximize the benefit for the client by minimizing the bill and reducing losses by optimizing the energy distribution in the network. There exist two smart grid management problems: demand side management (DSM) and dynamic economic dispatch (DED). DSM consists of modifying electricity consumption patterns with reference to the overall consumption picture, consumption time profile, and contractual supply parameters in order to achieve savings in electricity charges. DED aims at providing the ideal share of electricity produced corresponding to the overall energy request of users and the generated power. Research works in the literature dealt with DSM or DED issues independently. In this work, genetic algorithms will be used to solve DSM and DED problems, considering them as two complementary stages in the optimization process.

Keywords: smart grids; energy management; optimization; genetic algorithms

Citation: Dassa, K.; Recioui, A. Demand Side Management and Dynamic Economic Dispatch Using Genetic Algorithms. *Eng. Proc.* **2022**, *14*, 12. https://doi.org/10.3390/engproc2022014012

Academic Editors: Hamid Bentarzi and Fatma Zohra Dekhandji

Published: 30 January 2022

1. Introduction

Smart grid is a modernized electricity network that functions based on a two-way communication link. Smart grids, in addition to supporting utility companies in preserving energy, lowering expenditures, and raising network intelligibility, durability and effectiveness, encourage user involvement. Smart power managing encompasses the plan–control–optimize energy acts via intelligent responses or sophisticated equipment with the final goal to enhance production and ease, as well as to lessen the electricity price and emissions [1].

Demand side management (DSM) refers to plan and control actions that would in one way or another influence the end customer request in energy. The aim of the DSM plan is to reduce costs of electricity, which in turn restricts the need for building more transmission and distribution networks [2]. Various DSM strategies have been suggested and implemented. These include—energy conservation and energy efficiency, energy consumption optimization and scheduling, demand response, distributed generation, and energy storage [3,4]. To shape the end used energy consumption profile, a lot of mechanisms exist. Practical approaches are comprised of peak clipping, basin fill up, intentional preservation, consumption transferring, and time-reallocation [5,6].

With the advances in computers, computing techniques have been applied to the DSM problem. These techniques include artificial neural network, fuzzy logic and metaheuristic computation [7]. A user-adapted scheme is built up to tune the consumer's altering favorites in [8]. An HVAC system has been managed via fuzzy logic concepts with the efficacy contrasted with the traditional on–off counterpart in [9]. An intelligent HEMS using fuzzy logic to control storage and demand is proposed in [10]. An hourly energy consumption predictor [11] is developed using a multilayer perceptron. Artificial neural networks were deployed to predict DR and electricity request profile to sustain an intelligent house that is energetically efficient [12–14]. An optimized electricity planner for consumption reliability was studied with the optimization task resolved via PSO [15]. An online energy organizer for intelligent house electricity management, considering renewable sources and battery systems, was built up in [16]. A consumption prediction for a whole day was assumed prior to optimized planning with a joint Harmony Search-PSO approach via an HMI, inner manager, and various consumption levels [17]. A two-stage profound strengthening training strategy for domestic device planning besides incorporating charging and discharging schedules of energy storage and EV has been presented in [18]. On the other hand, economic dispatch refers to the share of total energy generation within existing distributed generators. Online active planning refers to online dynamic economic dispatch (DED) of energy and aims at minimizing the overall operating fuel cost and fulfilling the energy request in each time interval. Optimization techniques for solving the DED problem have been applied in the literature. Examples include artificial immune system algorithm [19], genetic algorithms [20], artificial bee colony [21], and particle swarm optimization [22,23].

The purpose of this paper is to illustrate Smart Grid management problems in order to maximize the benefit for the consumer. The aim is to minimize the bill and reduce losses. We will be using genetic algorithms to solve DSM and DED problems by considering them as two complementary stages in the optimization process.

2. DSM Optimization (First Stage)

Demand side management is one of the main elements in smart grids and has many advantages to both utility and users. Its goal is to wisely employ the existing electricity to enhance the financial matters of the grid. Controlling the energy profile may cut down on the maximum energy request, and hence enhance the efficacy of the power system, lowering hazardous emissions and energy cost for consumers.

Here, a DSM approach utilizing load shifting method considering several kinds of domestic devices at different time slots in order to minimize a cost function, along with the equality and inequality restraints to reach energy bill maximum and decrease the Max to Typical Quotient. The load scheduling problem is formulated as follows:

$$min\ f = \sum_{t=1}^{t=24} \sum_{a=1}^{n} \sum_{b=1}^{m} Xab(t) * Eab(t) * EP(t) \quad (1)$$

$$min\ f = \sum_{t=1}^{t=24} \sum_{a=1}^{n} \sum_{b=1}^{m} Xab(t) * Eab(t)\ \leq L(t) \quad (2)$$

ma = $24 - la$; Yab = $0\forall 24 - li > ma$; $Yab > 0\forall$a, b

$$\sum_{t=1}^{24} Ctbab \leq A(t) \quad (3)$$

where: 't' represents time slots; 'a' is the number of appliances. 'b' is the type of appliance; 'Xab' is ON/OFF state of appliance of type 'b', 'Eab' is the energy consumption of appliance 'a' of type 'b', 'EP' is the electricity price at time slot 't', ma is maximum permissible delay of appliance b. la is the Number of ON request of appliances, i.e., length of operation time. $L(t)$ is maximum power limit at time slot t; and Yab is controllable appliance of type b.

$A(t)$ is set of controllable appliances at time slot b.

To illustrate the efficacy of the adopted approach, the scheme is applied on two unlike regions: residential and commercial areas. The regions have diverse kinds of controllable appliances, as detailed in Tables 1 and 2.

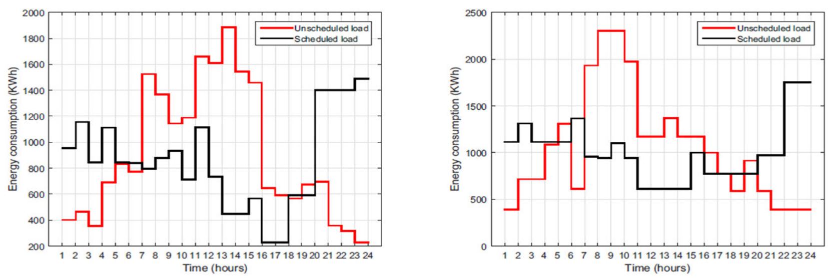
Table 1. Controllable devices in residential area.

Device	Power Consumption (kWh)	Number of Devices
Dryer	1.2	189
Dish Washer	0.7	288
Wshing Machine	0.5	268
Oven	1.3	279
Iron	1.0	340
Vacuum Cleaner	0.4	158
Fan	0.2	288
Kettle	2.0	406
Toaster	0.9	48
Rice-Cooker	0.85	59
Hair Dryer	1.5	58
Blender	0.3	68
Frying Pan	1.1	101
Cofee Maker	0.8	56
Total	–	2604

Table 2. Controllable devices in commercial area.

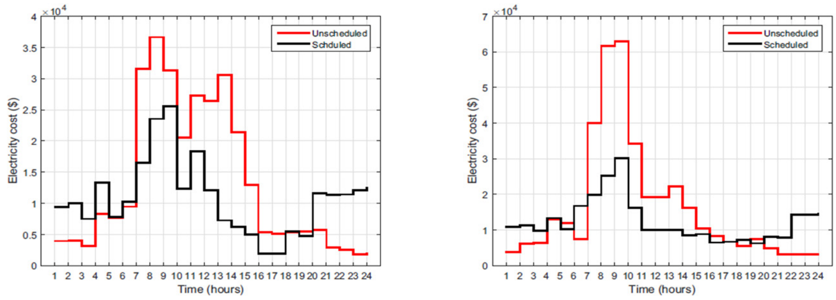
Device	Power Consumption (kWh)	Number of Devices
Water Heater	12.5	39
Welding Machine	25	35
Fan/AC	30	16
Arc Furnace	50	8
Induction Motor	100	5
DC motor	150	6
Total	–	109

It is clear from Figure 1a that the peak load of the residential area has been reduced by about 21.04%. Residential users schedule their maximum load where the price is low, which leads to minimize the electricity bill, as shown in Figure 1c. Indeed, the electricity bill has been reduced from 311,290 $ to 257,940 $ per day, which accounts for about a 17.1382% reduction.



(**a**) (**b**)

Figure 1. *Cont.*



(**c**) (**d**)

Figure 1. Optimization results: (**a**) Residential area daily energy consumption. (**b**) Commercial area daily energy. (**c**) Residential area daily electricity bill. (**d**) Commercial area daily electricity bill.

For the commercial area, peak load is reduced, where it used to be 1752 kW, it is now 2301 kW, which means a reduction of about 23.85% in max. consumption, as shown in Figure 1c. The electricity bill used to be 380,650 $ and has been lowered to 297,040 $ a day, which translates to about a 21.9647% reduction in the electricity bill per day as seen in Figure 1d.

3. ED Optimization (Second Stage)

This stage will use the best adequate sharing of appliances utilized by consumers at various time intervals obtained from the 1st optimization stage. To keep the price and electricity simultaneously at their minimum values, this second phase considers the following cost function:

$$min\ f2 = \sum_{i=1}^{t}(\sum_{u=1}^{m}(\sum_{s=1}^{S}\left(X(s)_{i,u} \times E_s(i) \times C_s(i) \times d_{u,s}\right))). \tag{4}$$

where: $X(s)_{i,u}$ is the share of electricity obtained from generator 's' to consumer 'u' during inteval 't'. $E_s(i)$ is the electricity from source 's' in the interval 'i' (kWh). $C_s(i)$ is the corresponding price (\$/kWh). $d_{u,s}$ is a parameter to account for losses due to the Joule effect and depends on the relative location of consumer and electricity generator.

The equality constraint equation is defined by:

$$\begin{aligned}&\sum_{s=1}^{S} X(s)_{i,u} \times E_s(i) = \sum_{a=1}^{n}\left(y(i)_{a,u} \times P_{shif}(i)_{a,u} \times \Delta t_{a,u} + P_{unshift}(i)_{a,u} \times T\right).\\ &\forall\ i\ \epsilon\{1,2\ldots t\}\ and\ \forall\ u\ \epsilon\{1,2\ldots m\}\end{aligned} \tag{5}$$

where: n is the number of electrical devices. $P_{shif}(i)_{a,u}$ *and* $P_{unshift}$ are the energy consumed by scheduled and nonscheduled appliances, respectively, in (kW). $\Delta t_{a,u}$ is the time of use for appliance 'a' utilized by consumer 'u' in the interval multiplied by 'i' (hours). $\Delta t_{a,u}$ can take values smaller or equal to the time length T.

In this section, we took 5 users, 5 devices, 32 total device numbers, 4 slots of time and 3 different energy sources.

Step 1 (selection): introducing the required input data randomly, generating the initial population of chromosomes that is called parents that contribute to the population of the next generation. Evaluate the equality constraint, if any chromosome violates the problem's constraints, it will be replaced by another randomly selected one.

Step 2 (fitness selection): This step concerns the objective function calculation for the potential solutions in the chosen group. The smallest objective function value with respect to the evaluation obtained in the preceding iterations is regarded as a first best result of the optimization process. More fit individuals are more likely to be selected.

The optimized energy profile for each consumer at each time interval will be fulfilled by three unlike generators: PV, wind and fossil fuel energy, for the sake of establishing in each time interval the best combination with respect to the share of each power generator to fulfill each consumer in the time interval, all at the lowest price with the least electricity losses in the network.

In the foremost time interval, the share of each generator to fulfill each consumer is presented in Figure 2. In this time interval, electricity is delivered to consumers 1, 3, 4 and 5 from the wind generator and the grid, as no electricity is supplied from generator 1 (PV), at a relatively smaller importance for the grid generator, as it is cheaper compared to the wind generation in this time interval.

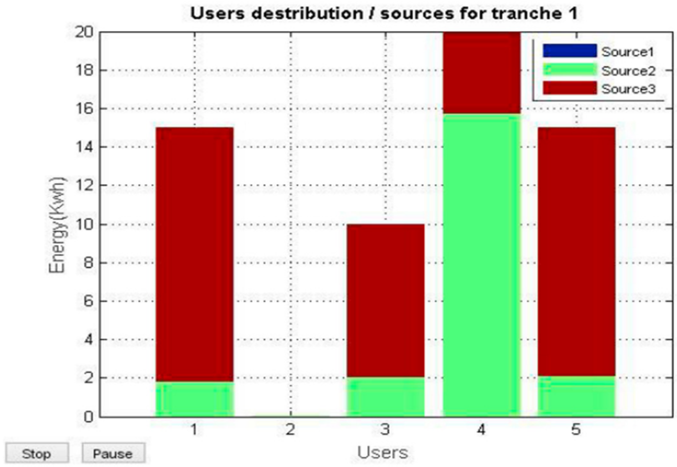


Figure 2. Share of electricity generation for various consumers for time interval 1 (tranch ′*i* = 1′).

For the second time interval, Figure 3 illustrates the generated electricity for each consumer using the three generators and PV and grid generators show dominance. This is because the electricity generation prices of these generators are at (0.5$/kWh), which makes them cheaper than the cost of electricity generated by wind (0.7$/kWh).

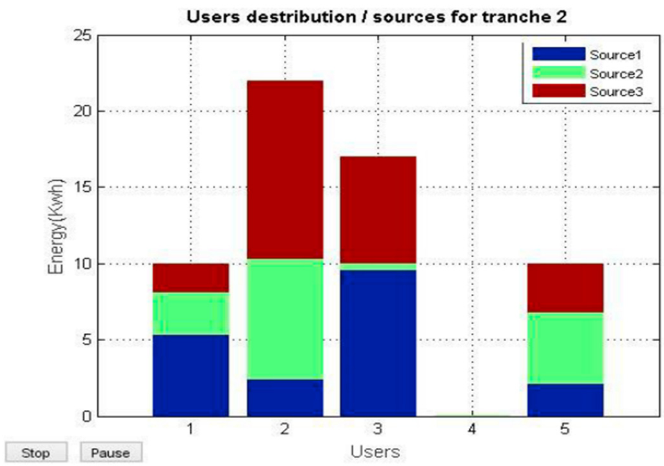


Figure 3. Share of electricity generation for various consumers in time interval 2 (tranch ′*i* = 2′).

In the time interval 3, the price of electricity from the wind generator is lower than that of the PV generator, causing the dominance of the wind and grid generators as shown in Figure 4.

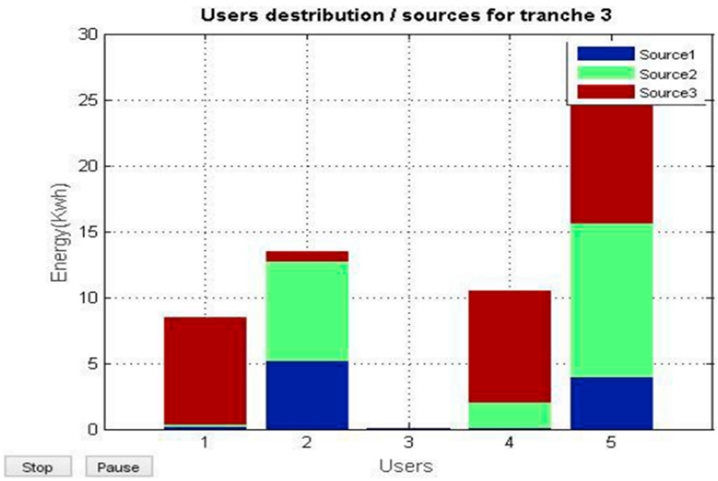


Figure 4. Share of electricity generation for various consumers in time interval 3 (tranch 'i = 3').

Finally, the best share for the time interval 4 is related to consumer 5 only, who is fed from the wind and grid generators at a remarkable dominance of the wind generator, as shown in Figure 5. It is worth noting that these findings concern not only the electricity price, but also the cost of electricity losses while transmitting from generators to consumers via the distance parameters as well.

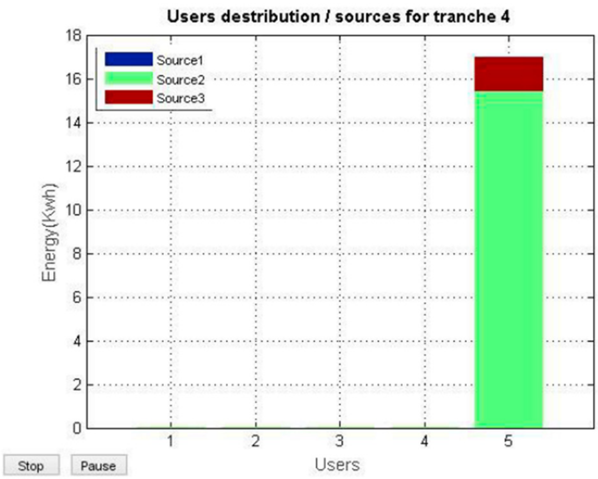


Figure 5. Share of electricity generation for various consumers in time interval 4 (tranch 'i = 4').

4. Conclusions

This work considers a set of users in two different regions employing many scheduled electrical appliances and supplied from various electricity generators. These generators exhibit variable electricity and production cost patterns at four daily time intervals. The planned electricity usage pattern for each region is dealt with separately for the sake of obtaining the best share of appliance usage time at various intervals to keep away from excessive consumption situation. At this situation, maximum values for the cost coefficient are adopted. The findings are then blended by computing the share of each power generator at each time interval. The results demonstrate the practicability of the adopted procedure with respect to the traditional non-planned techniques when considering both DSM and DED problems.

Author Contributions: Conceptualization, A.R.; methodology, K.D.; software, K.D.; validation, A.R., and K.D.; formal analysis, A.R.; investigation, K.D.; resources, K.D.; data curation, K.D.; writing—original draft preparation, K.D.; writing—review and editing, A.R.; visualization, K.D.; supervision, A.R.; project administration, A.R.; funding acquisition, A.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ahmad, Z.; Abbasi, M.H.; Khan, A.; Mall, I.S.; Khan, M.F.N.; Sajjad, I.A. Design of IoT Embedded Smart Energy Management System. In Proceedings of the 2020 International Conference on Engineering and Emerging Technologies (ICEET), Lahore, Pakistan, 22–23 February 2020; pp. 1–5.
2. Recioui, A.; Bentarzi, H. *Optimizing Smart Grid Operation and Control*; IGI Global: Hershey, PA, USA, 2021.
3. Recioui, A.; Djemai, H.; Boucenna, F. A Smart Metering Simulation in LABVIEW. *Alg. J. Sig. Syst.* **2019**, *4*, 89–100. [CrossRef]
4. Recioui, A.; Dekhandji, F.Z. Implementation of Load Control for Smart Metering in Smart Grids. In *Optimizing and Measuring Smart Grid Operation and Control*; IGI Global: Hershey, PA, USA, 2021.
5. Azzougui, Y.; Recioui, A. Hardware and software load power control in smart home applications based on Taguchi optimisation technique. *Int. J. Intell. Syst. Des. Comput. Indersci.* **2018**, *2*, 203–223.
6. Recioui, A. Home Load-Side Management in Smart Grids Using Global Optimization. In *Research Anthology on Multi-Industry Uses of Genetic Programming and Algorithms*; IGI Global: Hershey, PA, USA, 2021.
7. Vesselényi, T.; Moldovan, O.; Bungau, C.; Csokmai, L. A survey on soft computing techniques used in intelligent building control. *Recent Innov. Mechatron.* **2014**, *1*. [CrossRef]
8. Keshtkar, A.; Arzanpour, S. An adaptive fuzzy logic system for residential energy management in smart grid environments. *Appl. Energy* **2017**, *186*, 68–81. [CrossRef]
9. Anastasiadi, C.; Dounis, A.I. Co-simulation of fuzzy control in buildings and the HVAC system using BCVTB. *Adv. Build. Energy Res.* **2018**, *12*, 195–216. [CrossRef]
10. Krishna, P.N.; Gupta, S.R.; Shankaranarayanan, P.; Sidharth, S.; Sirphi, M. Fuzzy Logic Based Smart Home Energy Management System. In Proceedings of the 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Bengaluru, India, 10–12 July 2018; pp. 1–5.
11. Wahid, F.; Ghazali, R.; Fayaz, M.; Shah, A.S. Statistical Features Based Approach (SFBA) for Hourly Energy Consumption Prediction Using Neural Network. *Int. J. Inf. Technol. Comput. Sci.* **2017**, *9*, 23–30. [CrossRef]
12. Lu, R.; Hong, S.H.; Yu, M. Demand Response for Home Energy Management Using Reinforcement Learning and Artificial Neural Network. *IEEE Trans. Smart Grid.* **2019**, *10*, 6629–6639. [CrossRef]
13. Hafeez, G.; Alimgeer, K.S.; Wadud, Z.; Khan, I.; Usman, M.; Qazi, A.B.; Khan, F.A. An Innovative Optimization Strategy for Efficient Energy ManagementWith Day-Ahead Demand Response Signal and Energy Consumption Forecasting in Smart Grid Using Artificial Neural Network. *IEEE Access* **2020**, *8*, 84415–84433. [CrossRef]
14. Yousefi, M.; Hajizadeh, A.; NorbakhshSoltani, M.; Hredzak, B. Predictive Home Energy Management System with Photovoltaic Array, Heat Pump and Plug-in Electric Vehicle. *IEEE Trans. Ind. Inf.* **2020**, *17*, 430–440. [CrossRef]
15. Ren, Y.; Wu, H.; Yang, H.; Yang, S.; Li, Z. A Method for Load Classification and Energy Scheduling Optimization to Improve Load Reliability. *Energies* **2018**, *11*, 1558. [CrossRef]
16. Li, S.; Yang, J.; Song, W.; Chen, A. A Real-Time Electricity Scheduling for Residential Home Energy Management. *IEEE Internet Things J.* **2019**, *6*, 2602–2611. [CrossRef]
17. Zhang, Z.; Wang, J.; Zhong, H.; Ma, H. Optimal scheduling model for smart home energy management system based on the fusion algorithm of harmony search algorithm and particle swarm optimization algorithm. *Sci. Technol. Built Environ.* **2020**, *26*, 42–51. [CrossRef]
18. Lee, S.; Choi, D.H. Energy Management of Smart Home with Home Appliances, Energy Storage System and Electric Vehicle: A Hierarchical Deep Reinforcement Learning Approach. *Sensors* **2020**, *20*, 2157. [CrossRef] [PubMed]
19. Hatata, A.Y.; Hafez, A.A. Ant lion optimizer versus particle swarm and artificial immune system for economical and eco-friendly power system operation. *Int. Trans. Electr. Energy. Syst.* **2019**, *29*, e2803. [CrossRef]
20. Zou, D.; Li, S.; Kong, X.; Ouyang, H.; Li, Z. Solving the combined heat and power economic dispatch problems by an improved genetic algorithm and a new constraint handling strategy. *Appl. Energy* **2019**, *237*, 646–670. [CrossRef]
21. Secui, D.C. A new modified artificial bee colony algorithm for the economic dispatch problem. *Energy Convers. Manag.* **2015**, *89*, 43–62. [CrossRef]

22. Mahdi, F.P.; Vasant, P.; Watada, J.; Kallimani, V.; Abdullah-Al-Wadud, M. A quantum-inspired particle swarm optimization approach for environmental/economic power dispatch problem using cubic criterion function. *Int. Trans. Electr. Energy Syst.* **2018**, *28*, e2497. [CrossRef]
23. Elsayed, W.T.; Hegazy, Y.G.; El-Bages, M.S.; Bendary, F.M. Improved Random Drift Particle Swarm Optimization with Self-Adaptive Mechanism for Solving the Power Economic Dispatch Problem. *IEEE Trans. Ind. Inform.* **2017**, *13*, 1017–1026. [CrossRef]