VOL. 19, NO. 3, FEBRUARY 2024 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

MOTH FLAME OPTIMISATION FOR OPTIMAL POWER FLOW IN A POWER SYSTEM WITH STATIC VAR COMPENSATOR

P. Meenakshi, G. V. Nagesh Kumar, Vempalle Rafi, S. Hussain Vali, T. Obulesu and K. Ravisankar
Department of Electrical and Electronics Engineering JNTUA College of Engineering Pulivendula, Kadapa, India
E-Mail: vempallerafi@gmail.com

ABSTRACT

It consequently becomes imperative in the current transmission networks to make full use of existing resources and to rapidly transition to renewable energy alternatives. Electrical energy end users also benefit from effective resource utilisation since it lowers the price they pay for electricity. In this work, we offer a multi-objective optimum power flow (OPF) for an integrated gearbox network where FACTS devices are present. The paper's originality lies in the use of a multi-objective function. Minimising voltage variation, power loss, and negative social welfare (NSW) are all part of the objective function. The abatement of loss and NSW guarantees the lowering of per-unit pricing of power at the consumer end resulting in improved customer satisfaction. The problem was fixed using a FACTS Static var compensator. The theory was tested using an IEEE 30 bus network. The objective function has been optimised using the Mouth Flame Optimisation Algorithm. Detailed presentations, comparisons, and analyses of the collected findings have been made.

Keywords: optimal power flow (OPF), moth flame optimization (MFO), static var, negative social welfare (NSW).

Manuscript Received 16 November 2023; Revised 27 February 2024; Published 30 March 2024

1. INTRODUCTION

India has a huge population and a rapidly expanding need for electricity. Pressure on the country's transmission corridors has only grown since the deregulation of the electricity sector. Consequently, the optimisation of power flow has acquired great significance in the power business. To achieve the same level of efficiency as HVDC networks at a lower cost, the AC gearbox network must include FACTS devices.

The ABC approach is a kind of optimisation that takes inspiration from the coordinated foraging of honeybee colonies. Using an ORPF based on the ABC algorithm, this study explores how active power loss in power networks may be reduced [1]. However, the ABC method does not need external parameters like the cross-over rate and the mutation rate, unlike the genetic algorithm and differential evolution. To further improve the optimisation performance of GSA [2]. Inspired by grey wolves' leadership and hunting activities, this paper details the implementation of a unique meta-heuristic technique called the grey wolf optimizer (GWO) to solve the problem of optimal reactive power dispatch (ORPD). The ORPD problem is well-known as an example of a nonlinear optimisation problem in a power network [3]. Nonlinear optimisation problems with continuous and discrete parameters are required to determine the best method for distributing reactive power. The recommended method is used to optimise a given item by setting control variables such as generator voltages, tap locations of tap changing transformers, and wattles compensation components. In this investigation, we will consider how valve loading affects the challenging optimisation problem at hand. For this research, we plan to use a state-of-the-art SI technique known as Grey Wolf Optimizer (GWO). To prove that GWO is effective in fixing the ED problem with 13-unit and TAIPOWER 40-unit networks, we will compare its performance to that of other modern techniques [5]. This research proposes a natural-inspired algorithm dubbed Moth-Flame Optimisation (MFO) to address the Economic Dispatch (ED) problem. When determining the least expensive method of generating electricity, this research will take into account practical constraints including ramp rate restrictions, limited operation zones, and generator operating limits [6]. We propose an improved particle swarm optimisation (IPSO) that combines particle swarm optimisation with the chaotic sequences methodology, yielding superior results. Particle swarm optimisation is a powerful method for solving global optimisation problems. PSO employs chaotic sequences to improve global searches and provide a way out of local minima. [7]. This study presents a fresh genetic approach to the problem of economic dispatch in broad-extension power networks. A novel encoding technique has been refined. In this form of encoding, the incremental cost of the network is normalised and then encoded into the chromosome. This suggests that the total number of chromosomal bits has nothing to do with the scale [8]. The extended grey wolf optimiser (IGWO) refines the standard GWO to accelerate convergence by altering the exploration-exploitation balance. Weighted distance is used in the proposed IGWO to remedy this drawback of standard GWO. Size reactive power resources optimally are a non-linear, non-convex optimisation issue [9]. The optimum power flow (OPF) issue is solved using a modified Sine-Cosine algorithm in this study. This is tightly linked to non-linear constrained optimisation. MSCA reduces computing time and speeds up optimum solution and feasibility discovery [10]. The gravitational search algorithm (GSA) is suggested for solving the power network OPF issue. The suggested method can identify suitable OPF problem regulation settings [11]. The proposed approach was applied to the standard IEEE 30-bus test network to reduce fuel costs, improve the voltage profile, and increase voltage stability, and the results were compared. The results of the recommended technique are compared to current research [12]. This strategy improves standard SCA searching and compensates for its flaws. Goal functions include decreasing power losses, enhancing voltage profile, and stabilising the network. The proposed approach is tested on a 30-bus IEEE network and compared to standard optimisation algorithms [13]. An original optimisation paradigm, Moth-Flame optimisation (MFO), is created in this research. The moth's transverse orientation navigation technique provided the primary inspiration for this optimizer. When flying at night, moths maintain a constant wing angle relative to the moon, which allows them to cover great distances quickly and directly [14]. A well-placed SVC has the potential to reduce power loss by maintaining a constant voltage. The optimal placement of the SVC has been suggested using both the PSO technique and a fuzzy approach [15]. It has been proposed that incorporating SVC into SFLA might improve the voltage profile and cut down on active power loss [16]. By using MFO, the Optimal Power Flow issue was solved [17]. In this study, we implement the MFO method to reduce power loss by optimal device placement. This also determines the size of the control parameters used for the SVC. This technique is implemented and tested on a standard IEEE 14-bus network.

2. PROBLEM FORMULATION

OPF may lower the total fuel price of thermal units by regulating the active and reactive power output of generators, bus voltage, capacitor/shunt reactor, transformer tap adjustment, and gearbox line power flow. Limits arising from the physical laws regulating transmission networks, energy production and utilisation, and equipment limit all play a role in OPF, which is an optimisation problem with the objective function and certain constraints.

2.1 Objective Function

When developing OPF, reducing the cost of active power production was the primary focus. Additionally, the active power produced by each generating unit is reflected in a quadratic cost function. Next, the cost functions of each generator are summed to get the network's objective function.

$$F_c = min\left(\sum_{i=1}^{ng} a_i P_{Gi}^2 + b_i P_{Gi} + c_i\right) \tag{1}$$

2.1.1 Equality constraints

Objective 1: The goal of this item is to reduce the amount of energy that is lost as heat along electricity lines.

$$F_{PL} = min(P_{Loss}) = min\left(\sum_{k=1}^{ntl} real(S_{ij}^k + S_{ji}^k)\right) \tag{2}$$

Where

ntl: Number of transmission lines,

S_{ij}: Total complex power flow of line i^{th} bus - j^{th} bus

Objective 2: To get the necessary gearbox voltage, this Voltage Deviation (VD) aims to:

$$F_{VD} = \min(VD) = \min\left(\sum_{k=1}^{Nbus} |V_k - V_k^{ref}|\right) \tag{3}$$

Where

V_k: Voltage at bus k

V_k^{ref}: Reference voltage at bus k

Equality constraints:

$$P_{Gi} - P_{Di} = \sum_{j=1}^{N} |V_i||V_j||Y_{ij}|\cos(\theta_{ij} + \delta_j - \delta_i) \tag{4}$$

$$Q_{Gi} - Q_{Di} = \sum_{j=1}^{N} |V_i||V_j||Y_{ij}|\sin(\theta_{ij} + \delta_j - \delta_i) \tag{5}$$

Inequality constraints:

1) Voltage limits for generator buses:

$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}$, Gi=1, 2, 3... ngb

2) Real power generation limits:

$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}$ Gi=1, 2, 3... ngb

3) Reactive Power generated limits:

$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}$,Gi=1, 2, 3... ngb

4) SVC limit

$\mathbf{B}_{svc}^{min} \le \mathbf{B}_{svc} \le \mathbf{B}_{svc}^{max}$

3. MOTH FLAME OPTIMIZATION

This is a method of optimisation with roots in the natural world. The algorithm's design was inspired by the moths' method of navigating at night. The moths fly at a steady angle towards the moon. Moths often fly in spiral patterns around lights. The multi-objective function's solution is assumed to be represented by the moths. One of the parameters of the issue is the spatial distribution of the moths. The following is a summary of the mathematical models of moth behavior: In light of these constraints, we describe the logarithmic spiral used by the MFO method flow diagram shown in Figure-1, where S is the spiral function, Mi is the i^{-th} moth, and F_j stands for the j^{-th} flame.

$$M_i = S(M_i, F_I) \tag{6}$$

$$S(M_i, F_I) = D_i . e^{bt} . \cos(2\pi t) + F_j \tag{7}$$

Di is the distance between the ith moth and the jth flame, b is a constant used to define the shape of the logarithmic spiral, and t is a random number in the interval [-1, 1].

VOL. 19, NO. 3, FEBRUARY 2024 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

$$D_i = |F_j - M_i| \quad (8)$$

Where M_i is the i^{th} moth for the j^{th} flame and D_i is the distance between them.

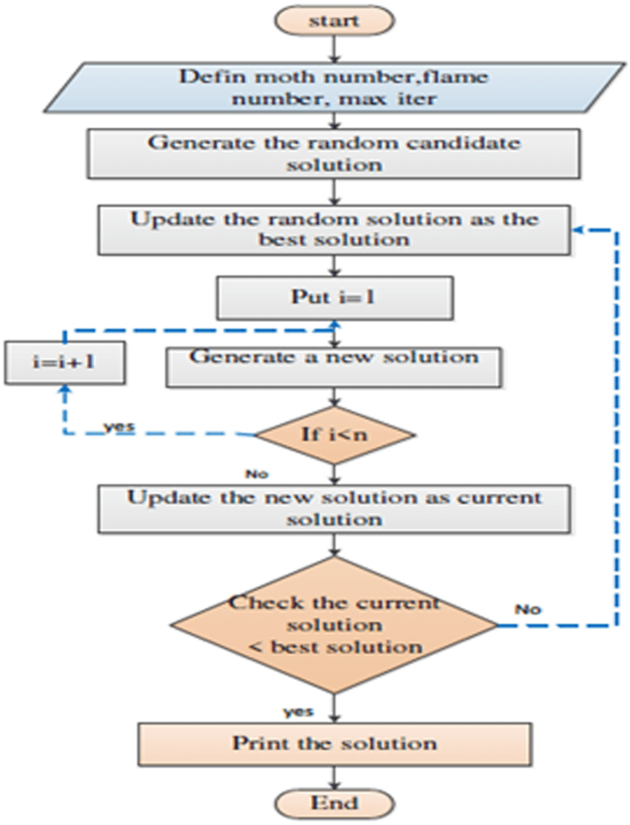

Figure-1. Flow chart of moth flame algorithm.

4. RESULTS AND DISCUSSIONS

In Figure-2, an IEEE 14 bus network with 11 transmission lines, 5 PV buses, 1 slack bus, and the remaining load buses is shown. The deployment of SVCs has been restricted to load buses only.

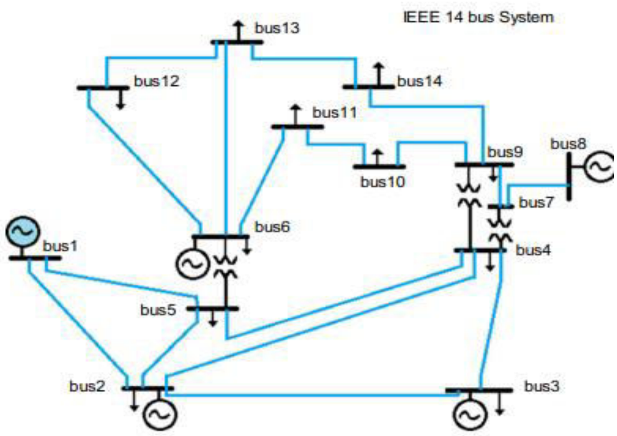

Figure-2. Block diagram of 14 bus networks.

VOL. 19, NO. 3, FEBRUARY 2024 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Table-1. Optimal power flow for IEEE 14 bus network without and with SVC devices by considering Fuel cost as an objective.

S. No	Parameter		Without FACTS devices	With SVC
1	Real power generation (MW)	P_{G1}	123.2919	103.9183
		P_{G2}	28.1229	20
		P_{G3}	20	20
		P_{G6}	54.7407	54.6947
		P_{G8}	89.9742	64.8891
2	Total Active power generation (MW)		310.8	310.8
3	Total real power generation cost ($/hr)		1250	1050
4	Active power Loss (MW)			4.5021
6	Voltage deviation (p.u.)		0.2503	0.1839
8	Objective function		FC	FC

Table-1 shows the considering fuel cost; the optimal power flow for an IEEE 14 bus network without SVC devices and with SVC devices has been calculated. Voltage profile comparison for IEEE 14 bus utilising MFO with and without FACTS devices indicates in Figure-3. Table-2 indicates the Optimal Power Flow for the IEEE 14 bus network without and with SVC by considering voltage deviation as an objective. Convergence characteristics of multi multi-objective function for the IEEE 14 bus using MFO are shown in Figure-4. Optimal Power Flow for IEEE 14 bus network without and with SVC by considering transmission losses as an objective indicated in Table-3 and Contrast of Voltage profiles with and without SVC for normal loading Table-4.

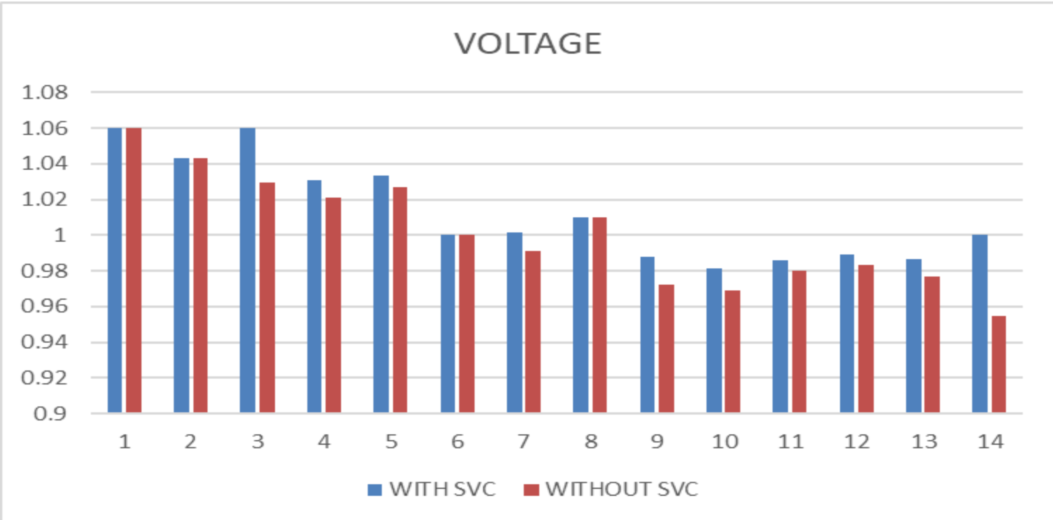

Figure-3. Contrast of voltage profile with and without FACTS devices for IEEE 14 bus using MFO.

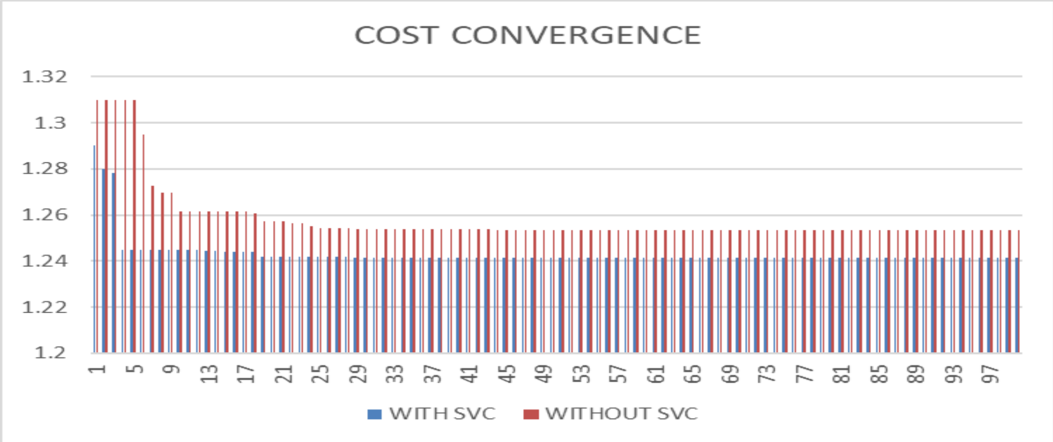

Figure-4. Convergence characteristics of multi-objective function for IEEE 14 bus using MFO.

Table-2. Optimal Power Flow for IEEE 14 bus network without and with SVC by considering voltage deviation as an objective.

S. No	Parameter		Without FACTS devices	With SVC
1	Real power generation (MW)	P_{G1}	10	10
		P_{G2}	180	180
		P_{G3}	150	150
		P_{G6}	12.5099	10.1580
		P_{G8}	10	10
2	Total Active power generation (MW)		310.8	310.8
3	Total real power generation cost ($/hr)		1770	1690
4	Active power Loss (MW)		51.7099	101.158
6	Voltage deviation (p.u.)		0.1692	0.155
8	Objective function		VD	VD

Table-3. Optimal Power Flow for IEEE 14 bus network without and with SVC by considering transmission losses as an objective.

S. No	Parameter		Without FACTS devices	With SVC
1	Real power generation (MW)	P_{G1}	11.6876	10
		P_{G2}	20	20
		P_{G3}	102.5732	98.0115
		P_{G6}	47.699	40.6750
		P_{G8}	130.000	91.2174
2	Total Active power generation (MW)		310.8	310.8
3	Total real power generation cost ($/hr)		1383.7	1160
4	Active power Loss (MW)		1.159	0.9038
6	Voltage deviation (p.u.)		0.3030	0.1814
8	Objective function		TL	TL

Table-4. Contrast of voltage profiles with and without SVC for normal loading.

Bus No.	MFO-OPF without SVC		MFO-OPF with SVC	
	Voltage magnitude (volt)	Voltage angle (deg)	Voltage magnitude (volts)	Voltage angle (deg)
1	1.06	0	1.06	0
2	1.0135	-2.5863	1.043	-4.5772
3	0.9834	-4.1154	1.0589	-0.2011
4	0.9654	-5.0462	1.0176	-9.2295
5	0.9256	-9.0823	1.01	-11.848
6	0.95	-6.1543	1.0148	-9.8282
7	0.9248	-7.8304	0.9988	-11.065
8	0.937	-6.4309	1.01	-10.265
9	0.9405	-7.927	1.026	-10.533
10	0.8962	-11.1654	1.004	-12.747
11	1.0201	-4.1979	1.082	-7.3115
12	0.9092	-8.93	1.0293	-12.149
13	0.908	-6.0138	1.071	-9.9661
14	0.8913	-10.387	1.0119	-13.070

CONCLUSIONS

The OPF issue was addressed in this article by using the Meta heuristic algorithm MFO. To begin, we want to refine the genetic algorithms framework so that we can connect fluctuations in the amount of power flowing through the network's wires to corresponding shifts in the output of individual generators. Concurrently verify the criteria for creating flow power in the network for each variable and in case the produced minimum point breaks the requirements, the procedure will be repeated. It is possible to determine the market price of electricity and the profit of generators by verifying the capacity of lines, which will be reported together with the power of generating units, network losses, bus voltage, generation cost, and power transmitted across those lines. Congestion-free network lines are a major concern in OPF. The simulation results demonstrate that the MFO algorithm performs well in comparison to the approaches used in literature, resulting in lower losses, less processing time, lower generating costs, and an OPF that is more in line with reality.

REFERENCES

[1] Ayan K., Kiliç U. 2012. Artificial bee colony algorithm solution for optimal reactive power flow. Appl Soft Comput J. 12(5): 1477-1482.

[2] Shaw B., Mukherjee V., Ghoshal S. P. 2014. Solution of reactive power dispatch of power networks by an opposition-based gravitational search algorithm. Int J Electr Power Energy Syst. 55: 29-40.

[3] Sulaiman M. H., Mustaffa Z., Mohamed M. R., Aliman O. 2015. Using the gray wolf optimizer for solving optimal reactive power dispatch problems. Appl. Soft Comput J. 32: 286-292.

[4] Khazali A. H., Kalantar M. 2011. Optimal reactive power dispatch based on the harmony search algorithm. Int. J Electr Power Energy Syst. 33(3): 684-692

[5] Sulaiman M. H., Ing W. L., Mustaffa Z., Mohamed M. R. 2015. Grey wolf optimizer for solving economic dispatch problem with valve-loading effects. ARPN J Eng Appl Sci. 10(21): 9796-9801.

[6] Sulaiman M. H., Mustaffa Z., Rashid M. I. M., Daniyal H. 2018. Economic dispatch solution using moth-flame optimization algorithm. In: MATEC web of conferences. Vol. 214.

[7] Park J-B, Jeong Y-W, Lee W-N, Shin J-R. 2008. An improved particle swarm optimization for economic dispatch problems with non-smooth cost functions. 20(1): 7.

[8] Chen P-H, Chang H-C. 2002. Large-scale economic dispatch by genetic algorithm. IEEE Trans Power Syst. 10(4): 1919-1926.

[9] Taha I. B. M., Elattar E. E. 2018. Optimal reactive power resources sizing for power network operations

enhancement based on improved grey wolf optimiser. IET Gener Transm Distrib. 12(14): 3421-3434.

[10] Attia A. F., El Sehiemy R. A., Hasanien H. M. 2018. Optimal power flow solution in power networks using a novel Sine-Cosine algorithm. Int. J Electr Power Energy Syst. 99(January): 331-343.

[11] Duman S., Güvenç U., Sönmez Y., Yörükeren N. 2012. Optimal power flow using a gravitational search algorithm. Energy Convers Manag. 59: 86-95.

[12] Abido M. A. 2002. Optimal power flow using particle swarm optimization. Int J Electr Power Energy Syst. 24(7): 563-571.

[13] Abdel-Fatah S., Ebeed M., Kamel S. 2019. Optimal reactive power dispatch using modified sine cosine algorithm. In: Proceedings of 2019 international conference on innovation trends computer engineering, ITCE 2019, no February. pp. 510-514.

[14] Mirjalili S. 2015. Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. Knowledge-based networks. 89, pp. 228-249.

[15] Yang W., Zhu W., Du B., Wang H., Xu L., Xie C., Shi Y. 2023. In the present work the microwave assisted oxidative desulfurization (ODS) of model light fuel oil in a helical coil reactor was investigated experimentally and numerically. Automotive waste heat recovery, Energy. 282, art. No. 128400.

[16] Zand M., Nasab M. A., Padmanaban S., Maroti P. K., Muyeen S. M. 2023. To improve the power generation efficiency of the ATEG in automobiles, a scheme is proposed to use a silicone polymer-based thermal conductive oil to transfer heat from the exhaust. Based on this concept, a new type of concentric tube heat exchanger is designed. Energy Reports. 10, pp. 431-438.

[17] Chen S., Hu M., Lei Y., Kong L. 2023. This paper expresses economic flexible-securable operation (EFSO) in smart distribution networks (SDNs), including distributed generation and storage networks to produce green energy. Applied Energy. 348, art. No. 121557.

[18] Dehghan M., Zadeh Bagheri M., Kiani M. J., Negation S. 2023. The traditional fuel locomotive is the primary type of locomotive currently in operation on non-electrified railways; however, it presents certain disadvantages including a low efficiency and high fuel consumption. Virtual power plants planning in the distribution network constrained to network resiliency under extreme weather events, Energy Reports. 9, pp. 4243-4256.

[19] Vempalle Vempalle Rafi, P. K. Dhal, M. Rajesh, D. R. Srinivasan, M. Chandrashekhar N. 2023. Madhava Reddy, Optimal placement of time-varying distributed generators by using crow search and black widow - Hybrid optimization, Measurement: Sensors. Vol. 30.

[20] Rafi Vempalle and P. K. Dhal. 2020. Loss Minimization by Reconfiguration along with Distributed Generator Placement at Radial Distribution System with Hybrid Optimization Techniques, Technology and Economics of Smart Grids and Sustainable Energy. Vol. 5.