

Rationale and State of the art

Development and society growth entail a proportional increase in electricity demand, which may be satisfied either by using a combination of electricity generation methods employing the resources available locally, or in the worst of the scenarios, importing it from another country.

In Colombia, nearly two-thirds of the total energy is produced by means of hydraulic generation (Unidad de Planeación Minero Energética, 2013), which is usually considered in literature as a clean and renewable technology. However, when dams are used as in most of hydroelectric centrals in Colombia, the place where the dam was built cannot be reused for agriculture or cattle raising (Killingtveit, 2014). This has negative impacts on ecosystems and biodiversity. Greenhouse gases effects on hydro-generation are often negligible (Killingtveit, 2014), except when the amount of decaying organic matter flooded in the dam is high enough to noticeably increase gases level.

On the other hand, in dry weather seasons thermal generation becomes more important, employing coal or natural gas as fuel, and comprising about 30% of the total installed capacity of the Colombian power system (Unidad de Planeación Minero Energética, 2013). Thermal generation represents a detrimental effect on environment since such production method brings about great amounts of greenhouse gases emissions (Killingtveit, 2014). The consideration of both environmental impact and additional economic cost of new power-generation projects and its integration to the grid, makes desirable an optimal use of electric energy and installed electrical capacity.

Traditionally, electricity demand is modeled in an aggregated form as a load curve showing load peaks in specific hours and a minor consumption the rest of the time; its use has been widespread since more than two decades ago (Andersson, Jansson, & Klevås, 1989). Consumption peaks in a load curve imply the need of an installed maximum generation capacity, whose power would not be totally consumed the whole time.

Demand management implies the possibility of modifying users' consumption profiles either individually or as part of a variable group by means of economic or performance incentives. Such management can be modeled in various ways and by deploying several approaches, each one trying to gather and reflect upon the main technical and economical features and behaviors of the users (Bompard et al., 2005; Yang, Zhang, & Tong, 2006).

In the Colombian case some methods for industrial sector demand management using pricing initiatives and direct load control have been put forward. The study by Espitia Silva & Ramos Acevedo (2014) makes emphasis on the possible impact of the load curve of specific facilities. Also, Rivera (2013) analyzes the effect of a differential fee for non-regulated users of the industrial sector aiming to lower the load curve peaks charging the users a higher kWh price in peak hours; his study concludes that the feasibility of the load curve shifting from industrial customers greatly depends on the type of industry and the specific needs; it also points that in most cases the consumption does not have important variations during the day, differently from the behavior of the residential sector electricity demand.

Because of the natural complexity of the problem, some assumptions limiting the scope of the theoretical model used to predict the behavior of the users are usually made, without accurately analyzing the individual consumption of each one. This entails deviations from actual users' energy demand and behavior, and

errors that affect technical, commercial and management decisions aimed at satisfying demand (Baharlouei et al., 2013; Gelazanskas & Gamage, 2014; Samadi, Mohsenian-Rad, Schober, & Wong, 2012; Yang et al., 2006).

Various authors have treated the demand management problem with different approaches and mechanism propositions seeking for an optimal distribution of the demanded energy of a group of users using adequate incentives (Marden, Arslan, & Shamma, 2009; Mhanna et al., 2014). It is worth noticing that, in most cases, the validation has been only partially covered by simulations with moderately detailed models, without reaching a comparison with empirical or historical data, which would allow to draw conclusions about the usefulness of applying proposed mechanisms to a real system or part of it.

Recently Barreto et al. have proven the inefficiency of the electricity system comparing the users' behavior regarding to electricity consumption with the *tragedy of the commons*, (Barreto, Mojica-Nava, & Quijano, 2013; Barreto et al., 2014).³ In this research it is proposed a mechanism of indirect revelation that compares the convergence and incentives of some traditional population dynamics to achieve the efficiency of the system at certain cost (net positive incentives must be provided) depending on the users' particular preferences and the dynamic evolution of the system. Population dynamics expresses the evolution of the state of the society, as described by Sandholm in (Sandholm, 2010). The authors conclude that the mechanism requires subsidies of external origin at least during the transition period of the system to the optimal.

The equations stated for each dynamic, for a given population game are as follows:

Let $F: X \rightarrow \mathbf{R}^n$ be a population game with a set of pure strategies named $(S^1, \dots, S^p)$ with population masses $m_p \in \mathbf{Z}^+$ and X the state space. Each population $p \in P$ is large but finite and has Nm_p members, where $N \in \mathbf{Z}^+$ is called *population size*. The set of possible social states $X^N = \{x \in X: Nx \in \mathbf{Z}^n\}$ is a discrete grid in the state space X (Sandholm, 2010).

$F_i^p: X \rightarrow \mathbf{R}$ denotes the payoff function of the population p playing the strategy $i \in S^p$.

$\bar{F}^p(x)$ is the average payoff for the population p , i.e.,

$$\bar{F}^p(x) = \frac{1}{m^p} \sum_{i \in S^p} x_i^p F_i^p(x) \quad (1)$$

x_i^p is the social state of the population p playing the strategy i .

$\hat{F}_i^p$ is the excess payoff to strategy $i \in S^p$,

$$\hat{F}_i^p(x) = F_i^p(x) - \bar{F}^p(x) \quad (2)$$

1. Replicator dynamic:

³ The *tragedy of the commons* refers to a dilemma presented by Garrett Hardin in 1958. In the original case, several individuals sharing a common resource act in a selfish and rational way contrary to the best interests of the whole group by depleting the resource. The term may be used for describing a variety of behaviors in the society including exploitation of natural resources, and in the particular case, for the generation of electricity.

$$\dot{x}_i^p = x_i^p \hat{F}_i^p(x) \quad (3)$$

2. *Brown-Von Neumann-Nash dynamic:*

$$\dot{x}_i^p = [\hat{F}_i^p(x)]_+ - x_i^p \sum_{k \in SP} [\hat{F}_k^p(x)]_+ \quad (4)$$

$[\cdot]_+$ means the expression enclosed in brackets is positive.

3. *Smith dynamic:*

$$\begin{aligned} \dot{x}_i^p = & \sum_{j \in SP} x_j^p [F_i^p(x) - F_j^p(x)]_+ \\ & - x_i^p \sum_{j \in SP} [F_j^p(x) - F_i^p(x)]_+ \end{aligned} \quad (5)$$

4. *Logit dynamic:*

With noise level $\eta > 0$;

$$\dot{x}_i^p = \frac{\exp(\eta^{-1} F_i^p(x))}{\sum_{k \in SP} \exp(\eta^{-1} F_k^p(x))} - x_i \quad (6)$$

Implementation

From the mechanism presented by Barreto et al. (2013, 2014) it is analyzed the effect of variable energy cost in the final consumption profile of a group of users with similar preferences. This is the starting point for the proposal of a modification in the fitness function for addressing the behavioral changes associated to a stratified population, by decreasing in a fixed percent the utility of the users with higher energy use profiles.

Demand Management Game Theory Model

Demand management problem can be characterized as a game with a number of single or grouped users with specific preferences, a utility function related to a fitness function, and a population dynamics model which defines the set of differential equations that predict the system evolution. For the sake of simplicity, in the modifications made to the mechanism proposed by Barreto et al., it is used a set of Matlab software called PDtoolbox⁴ (Barreto, 2014) available under the BSD license.

The mechanism proposed by Barreto et al., (2014) considers that the load is analyzed in hourly time lapses, and for each agent i there is a profit function $U_i(\mathbf{q})$:

$$U_i(\mathbf{q}) = v_i(\mathbf{q}_i) - \sum_{t=1}^T q_i^t r(\|\mathbf{q}^t\|_1), \quad (7)$$

Where $q_i^t \geq 0$ is the amount of energy consumed by the user i in the t^{th} time interval (from a 24 h period); $\mathbf{q}_i = [q_i^1, \dots, q_i^T] \in \mathbf{R}_{\geq 0}^T$ is the daily consumption profile of user i ; $\mathbf{q}$ is the electricity consumption of the population; r the unitary price function and $\|\cdot\|_1$ is the l-norm.

$v_i(\mathbf{q}_i) = v(\mathbf{q}_i^k, \alpha_i^k)$ is the *valuation function*, i.e. the economic value given by the i^{th} user to his daily energy consumption, such that:

$$v(\mathbf{q}_i^k, \alpha_i^k) = v_i^k(q_i^k) = \alpha_i^k \log(1 + q_i^k) \quad (8)$$

Being $\alpha_i^k \geq 0$ a parameter that characterizes the valuation (of i^{th} agent at k^{th} time) of $q \geq 0$ power units, so that the valuation is increasing as α_i^k increases.

Incentives proposed are expressed as:

$$I_i(\mathbf{q}) = \|\mathbf{q}_{-i}\|_1 (h_i(\mathbf{q}_{-i}) - r(\|\mathbf{q}\|_1)) \quad (9)$$

Where $h_i(\mathbf{q}_{-i})$ estimates the electricity price when the i^{th} user does not take part in the electricity system and $\mathbf{q}_{-i}$ is a vector that represents the consumption of the population except for the i^{th} agent.

Adding incentives $I_i(\mathbf{q})$ to the profit function $U_i(\mathbf{q})$ for the i^{th} agent it is obtained the function in eq. (10):

$$W_i(q_i, \mathbf{q}_{-i}) = v_i(q_i) - q_i r(\|\mathbf{q}\|_1) + I_i(\mathbf{q}). \quad (10)$$

Then, the idea is to maximize customers benefit:

$$\begin{aligned} & \underset{\mathbf{q}_i}{\text{maximize}} && W_i(q_i, \mathbf{q}_{-i}) \\ & \text{subject to} && \sum_{t=1}^T q_i^t \leq Q_i. \end{aligned} \quad (11)$$

Where $N \in \mathbf{N}$ are the customers and $q_i^t \geq 0, i = \{1, \dots, N\}, t = \{1, \dots, T\}$

Resolving the optimization problem, the fitness function T_i^k that maximizes benefit of eq. (11) is:

$$T_i^k(\mathbf{q}^k) = \frac{\alpha_i^k}{1 + q_i^k} - 2\beta \left(\sum_{j=1}^N q_j^k \right) \quad (12)$$

With $\beta \geq 1$ a parameter related to the generation cost of electricity. According to (Barreto et al., 2014), this fitness function gets a Nash equilibrium state of the system after a transition period.

Base Simulation Results

Running the game for a 24h-daily- period with $P = 6$ populations, $Q_i = 50 \text{ kWh}$ and uniform initial conditions, α_i^k is chosen with an increased value for greater i assuming that users have different load profiles. The load profile shape for the test case is based on XM predictions for November 2014, in Fontibón's substation in Bogota, Colombia⁵. Incentives are introduced from 2 to 5 time units in a 30 time units simulation.

In figures 1 and 2 can be seen that varying β parameter, associated with the production cost of energy, users will tend to lower their power expenses, and will have less utility, related to the higher cost they will pay for energy. Also the convergence of the population is faster for most dynamics, as users will try to save costs.

⁵ Information available online on <http://www.xm.com.co/Pages/PronosticoOficialdeDemanda.aspx>

⁴ Population Dynamics Toolbox

In fig. 3 and 4 each line represents a group of users with similar preferences. It can be observed that users with lower valuation profiles will extra limit their consumption, according to the increased prices. It is not straightforward to select a dynamic over another among traditional ones, and should be convenient to establish some particular dynamics which best fit the population under analysis, which is still an open problem for the case of Bogotá population.

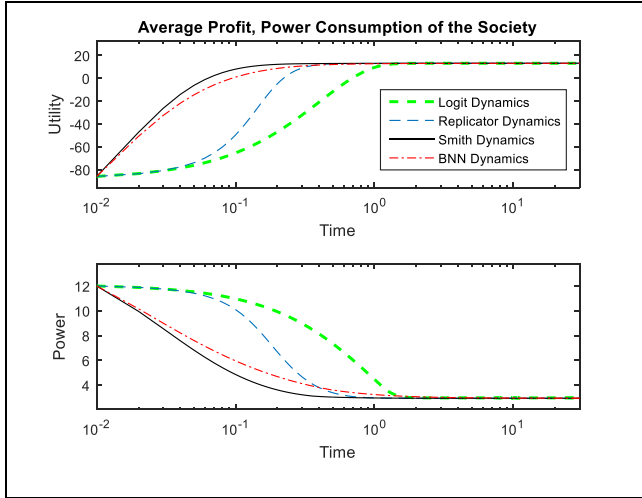


Figure 1. Average Utility and power evolution for various dynamics, with $\beta = 1$.

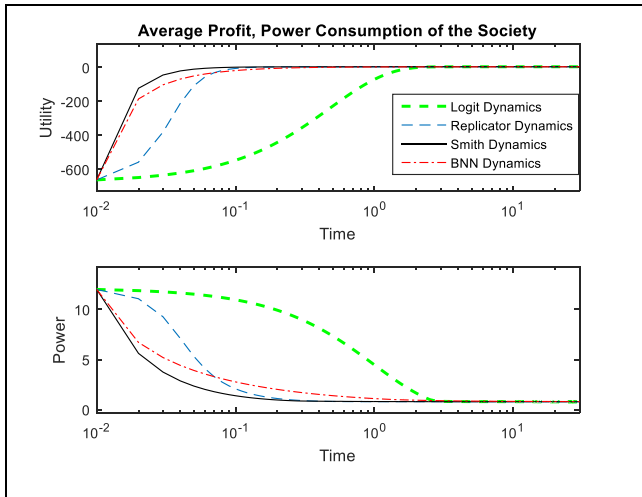


Figure 2. Average Utility and power evolution for various dynamics, with $\beta = 5$.

Mechanism Variation including Strata Consideration

Now, let introduce a variation in the fitness function associated to an added cost c_a proportional to the users valuation profile α_i^k , in order to make a basic implementation of socioeconomic strata, assuming that users in higher strata will have a higher consumption profile that it is desirable to have regulated, so that eq. (12) becomes:

$$F_i^k(\mathbf{q}^k) = \frac{\alpha_i^k}{1 + q_i^k} - (1 + c_a * \alpha_i^k) 2\beta \left(\sum_{j=1}^N q_j^k \right) \quad (13)$$

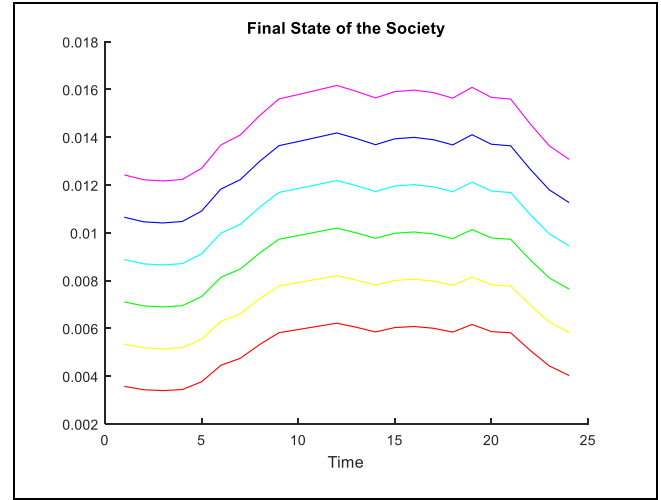


Figure 3. Final state of users, with $\beta = 1$.

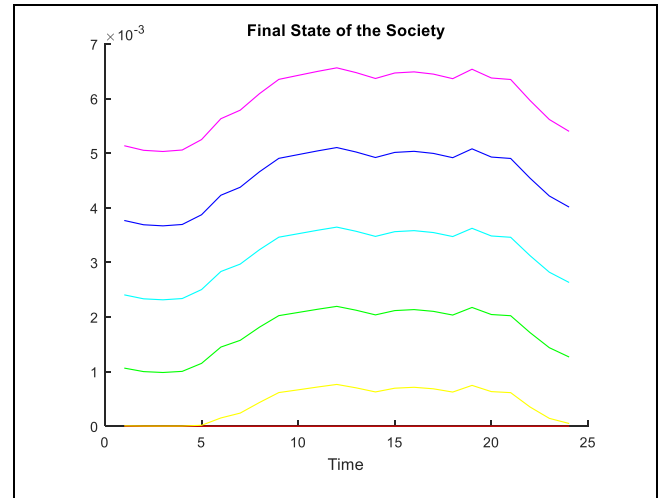


Figure 4. Final state of users, with $\beta = 5$.

The game was run maintaining all the conditions except for the added cost c_a , which was supposed as 10% and 30%. Hence, in figs. 5 to 8 the implications of the modification in the mechanism can be seen, for the game with every other condition kept the same. The total incentives for the population will increase or decrease depending on the population dynamics. It shows an important variation specially for Smith dynamic, where incentives' peak near the ending of the transition period gets lower as the added cost increases, getting overall lower incentives as well; Replicator dynamic has great variation too, extending the period where high incentives are demanded during the transition period when the added cost is greater.

As shown in fig. 5 and 6, the chosen dynamics greatly affects the amount of incentives used for the population in the transition to equilibrium process. This turns in a sensitive stage the selection of the population dynamics which best fit Bogotá's stratified population preferences and evolution in time.

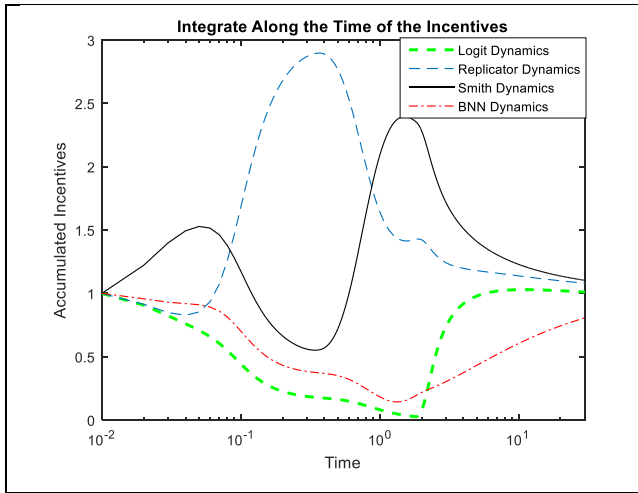


Figure 5. Cumulative incentives for the modified mechanism case, with added cost of 10%

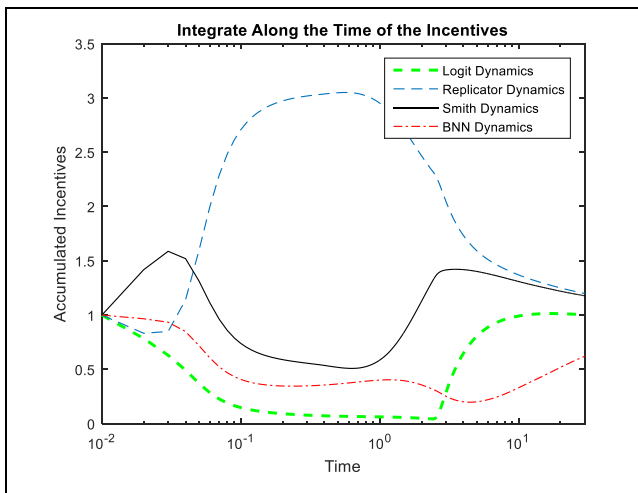


Figure 6. Cumulative incentives for the modified mechanism case, with added cost of 30%

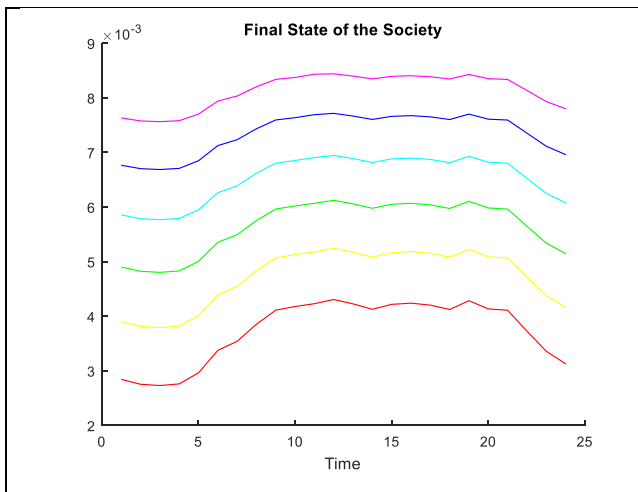


Figure 7. Final state of users, with $\beta=1$ and modified fitness function, with added cost of 10%

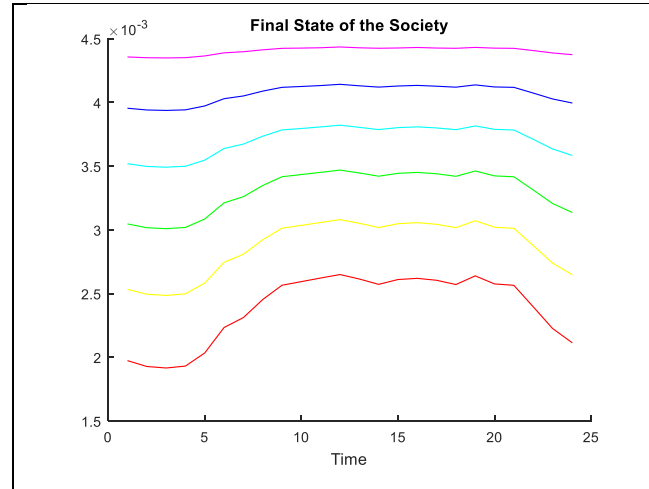


Figure 8. Final state of users, with $\beta=1$ and modified fitness function, with added cost of 30%

Equilibrium states of the society are shown in figures 7 and 8, where each line represents a group of users with the same consumption preferences, i.e. ranked in the same socioeconomic stratum. It is observed that all strata are affected by lowering their original consumption profile peaks shown in figure 3, having a flatter profile. The effect is specially marked for the users with greater valuation profiles which will become more homogeneous.

Conclusions

It has been reviewed the mechanism proposed by Barreto, Mojica-Nava, and Quijano (Barreto et al., 2013, 2014), analyzing variations of electricity generation cost as an introduction to the modification in the fitness function of the mechanism presented immediately after. The fitness function in the mechanism is associated to the maximum utility of the population, which may vary if the existence of users' economic strata is considered, as in the Colombian power system case.

The proposed modification of the mechanism leads to changes in incentives requirements during transition time before equilibrium state is reached, and also makes users with higher demand curve profiles to flatten their demand during the transition; thus obtaining a better energy distribution and use according to a central resource allocator entity. This variation of the mechanism sets the first stage of a much bigger project, and future work and research will be focused on addressing the particularization needed for the Colombian case including more variations and complexity for the incentives. Also, best fit population dynamics must still be derived for the actual behavior of Colombian users, as a whole or grouped in classes (strata).

Besides the best fit model and population dynamics which has to be proposed, it has to be taken into account comprehensive experimental data inclusion to the mechanism design for accurate characterization of real-world population. The experimental data may be historical records of consumption of just a part of the system, like Bogota, and shall be used for refinement and validation of the particularized mechanism.

The completed mechanism would state with sufficiency the rules and conditions needed to achieve a more efficient use of electricity, considering the necessary incentives, restrictions, and strata information of the users.

It would be interesting also take a complimentary approach considering the problem as a cooperative control game, as proposed by (Marden et al., 2009; Mojica-Nava, Barreto, & Quijano, 2015), associating a desired power usage for active agents with a consensus value, handling users stratification and comparing feasibility of implementation in a real world population.

References

- Andersson, A., Jansson, A., & Klevås, J. (1989). Model for load simulations by means of load pattern curves. In 10th International Conference on Electricity Distribution, CIRED (Vol. 6, pp. 545–549). Brighton: IEEE. Retrieved from <http://ieeexplore.ieee.org/articleDetails.jsp?arnumber=206140>
- Baharlouei, Z., Hashemi, M., Narimani, H., & Mohsenian-Rad, H. (2013). Achieving Optimality and Fairness in Autonomous Demand Response: Benchmarks and Billing Mechanisms. *IEEE Transactions on Smart Grid*, 4(2), 968–975. Retrieved from <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6476052>
- Barreto, C. (2014). Population Dynamics Toolbox. Retrieved from https://github.com/carlobar/PDToolbox_matlab
- Barreto, C., Mojica-Nava, E., & Quijano, N. (2013). Design of mechanisms for demand response programs. In 52nd IEEE Conference on Decision and Control (pp. 1828–1833). IEEE. Retrieved from <http://ieeexplore.ieee.org/articleDetails.jsp?arnumber=6760148>
- Barreto, C., Mojica-Nava, E., & Quijano, N. (2014, August 22). Incentives-Based Mechanism for Efficient Demand Response Programs. Cornell University Library. Retrieved from <http://arxiv.org/abs/1408.5366>
- Bompard, E., Carpaneto, E., Ciwei, G., Napoli, R., Benini, M., Galanti, M., & Migliavacca, G. (2005). A game theory simulator for assessing the performances of competitive electricity markets. In 2005 IEEE Russia Power Tech (pp. 1–9). IEEE. <http://doi.org/10.1109/PTC.2005.4524524>
- Espitia Silva, E. S., & Ramos Acevedo, D. A. (2014). Identificación de oportunidades para la gestión de la demanda en el sector industrial colombiano. Universidad Nacional de Colombia, Facultad de Ingeniería Eléctrica Y Electrónica. Trabajo de Grado Pregrado En Ingeniería Eléctrica. Bogotá.
- Gelazanskas, L., & Gamage, K. A. A. (2014). Demand side management in smart grid: A review and proposals for future direction. *Sustainable Cities and Society*, 11, 22–30. <http://doi.org/10.1016/j.scs.2013.11.001>
- Hurwicz, L., & Reiter, S. (2006). *Designing Economic Mechanisms*. Cambridge University Press.
- Killingtveit, Å. (2014). *Future Energy*. Elsevier. <http://doi.org/10.1016/B978-0-08-099424-6.00021-1>
- Marden, J. R., Arslan, G., & Shamma, J. S. (2009). Cooperative control and potential games. *IEEE Transactions on Systems, Man, and Cybernetics. Part B, Cybernetics: A Publication of the IEEE Systems, Man, and Cybernetics Society*, 39(6), 1393–1407.
- Mhanna, S., Verbič, G., & Chapman, A. C. (2014). Towards A Realistic Implementation Of Mechanism Design In Demand Response Aggregation. In 18th Power Systems Computation Conference. Wroclaw, Poland.
- Mojica-Nava, E., Barreto, C., & Quijano, N. (2015). Population Games Methods for Distributed Control of Microgrids. *IEEE Transactions on Smart Grid*, PP(99), 1–1. Retrieved from <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7145472>
- Rivera, B. (2013). Impacto de los precios de bolsa en los usuarios del servicio de energía eléctrica en el sector industrial. Universidad Nacional de Colombia, Departamento de Ingeniería Eléctrica Y Electrónica. Trabajo de Grado Pregrado En Ingeniería Eléctrica. Bogotá.
- Samadi, P., Mohsenian-Rad, H., Schober, R., & Wong, V. W. S. (2012). Advanced demand side management for the future smart grid using mechanism design. *IEEE Transactions on Smart Grid*, 3(3), 1170–1180.
- Sandholm, W. H. (2010). *Population Games and Evolutionary Dynamics*. MIT Press. Retrieved from http://books.google.com.co/books/about/Population_Games_and_Evolutionary_Dynamics.html?id=pZH6AQAAQBAJ&pgis=1
- Unidad de Planeación Minero Energética. (2013). Plan de Expansión de Referencia Generación – Transmisión 2013 – 2027 UPME. Bogotá. Retrieved from <http://www1.upme.gov.co/sala-de-prensa/fotonoticias/plan-de-expansion-de-referencia-generacion-transmision-2013-2027>
- Yang, H., Zhang, Y., & Tong, X. (2006). System Dynamics Model for Demand Side Management. In 2006 3rd International Conference on Electrical and Electronics Engineering (pp. 1–4). IEEE. Retrieved from <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=4017939>