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Research Article

Generation Expansion Models including Technical Constraints and Demand Uncertainty

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This article presents a Generation Expansion Model of the power system taking into account the operational constraints and the uncertainty of long-term electricity demand projections. The model is based on a discretization of the load duration curve and explicitly considers that power plant ramping capabilities must meet demand variations. A model predictive control method is used to improve the long-term planning decisions while considering the uncertainty of demand projections. The model presented in this paper allows integrating technical constraints and uncertainty in the simulations, improving the accuracy of the results, while maintaining feasible computational time. Results are tested over three scenarios based on load data of an energy retailer in Colombia.

1. Introduction

Decisions related to investments in power plants, known as Generation Expansion Planning (GEP), are often based on the load duration curve (LDC). Linear optimization models are already used for a long time to find the optimal mix of generation technologies supplying this demand. The LDC-based solutions describe the required installed generation capacity of each technology and their operating hours, in order to minimize the total cost, that is, the investment and operational cost. Since traditional models do not include the variations of the demand over time, they do not take into account the ramping and cycling capabilities of power plants. However, not including these technical constraints of power systems underestimates the flexibility needs of the system. This fact becomes increasingly relevant facing the rising trend of participation of renewable generation characterized by a variable profile of supply. Traditional approaches based on the LDC are not considering the potential value of flexibility provided by different generation technologies, and this results in a suboptimal solution. On the other hand, solutions that include these technical elements require high computational efforts. The fact that traditional solutions do not take into account the uncertainty of the demand forecast results in overcapacity or reliability issues regarding the installed capacity. As a consequence, suboptimal decisions of investments are associated with the long-term use of power plants.

The need to include technical constraints and uncertainty in the GEP requires the integration of new elements. However, these new elements increase the complexity of the problem. The same difficulty is faced while using scenarios which consider uncertainty but improve the ability to deal with long-term planning decisions and make the results robust in front of future trends in the power system. The state of the art in the generation investment problem shows different approaches to take the integration of new variables and uncertainties into account. A first set of approaches deals with the LDC model itself. In [1], a linear piecewise function is used to represent the German and UK LDC; a residual LDC is used to integrate renewable sources in the part of the curve where most changes of demand take place. Technical improvements such as ramp rates and the maximum on time of a generating units are suggested to be included in the LDC methodology [2]. In [3], a robust optimization that includes uncertainty of demand, the electricity price, and generation cost is proposed. A second set of approaches deals with the problem of technical constraints integration into the classical economic generation investment model, that is, based on the time series representation of the demand. Authors of [4] include several additional variables and constraints related to the power system to solve a single period problem. In [5], a relevant discussion about how dynamic constraints such as ramping rates and start-up cost are changing the optimal point of the classical generation investment solution is presented. The work stresses the need of methodologies exploring the solution in a prediction time horizon also called multiperiod solutions. A mixed solution proposed in [6] considers the integration of renewable generation in the GEP by means of net demand curve; to deal with prediction errors, an operating reserve constraint is imposed. The solution includes the ramp rate of the conventional technologies to cover the uncertainty of the wind generation power.

Finally, a set of detailed solutions makes use of stochastic and time series based models to solve the GEP. A generation plan expansion methodology using a multiperiod horizon solved by a bilevel problem is proposed in [7]. The problem maximizes the investment profits in the top level and the second level deals with technical constraints such as generation, transmission constraints, and load flows. The impact of renewable sources in the GEP is discussed in [8] with a model optimizing all the yearly investments, fixed and variable operational cost, reserve costs, and ramping and start-up costs constraints. The problem deals with a new optimal point to balance the increasing amount of renewable with reserves to meet the system reliability requirements. Last, in book [9], the long-term investments considering the GEP problem integrated with transmission investments are discussed. This book presents a full methodology based on stochastic processes. The solutions presented in this book take into account the integration of several planning horizons by means of multistage models with detailed technical constraints. Nevertheless, obtained results are based on decision trees and exhaustive solutions and, due to the very detailed models, results obtained in this book require a very high computational effort. Now, as explored in this review, time series and detailed solutions lead to use of complex methodologies that imply a high computational cost. The discussion of stochastic methods used to forecast power variables is not presented in this review. The scope of this state of art is to tackle the investment problem from the generation mix design. Concluding, new methodologies must deal with a trade-off between the detailed level and the required time to solve the problem in a large time horizon. Details are not paramount, planning exercises and scenarios analysis can use more efficiently solutions with less technical and forecast details. This work focuses on an optimal, flexible, and efficient multiperiod methodology to solve the GEP problem. The solution is inspired by the MPC (model predictive control) methodology. The solution includes ramping constraints creating a compromise between the power system flexibility and the installed capacity. This leads to a new optimal point which guarantees a reliable operation minimizing the fixed and variable investments cost. Four scenarios are simulated with uncertainties in the variables showing the advantages as a planning tool. The paper is organized as follows: Section 2 presents a brief description of the methodology. Sections 2.1 and 2.2 present the used LDC discretization and the dynamic analysis made to include the ramping constraints. Section 3 presents the comparison between the proposed model that includes the ramping constraints and the classic economic solution. Section 4 presents a brief description of the MPC and the approach used for the multiperiod GEP methodology. Lastly, Section 5 presents the used data, the test scenarios, and the model performance comparison of Section 3 finishing with the results of the MPC planning.

2. Methodology

As mentioned, the classic solution of the GEP based on the LDC only considers economic variables. Additionally, the method does not consider the time series of the demand to create the LDC information. New generation expansion plans should consider a wide selection of technologies and uncertainties; each technology has their own technical constraints and economic cost. An optimal temporal LDC partition allows distributing the GEP problem in several blocks or demand levels. Each level has his own features: required power, uncertainties, and power changes. Including the demand levels in the problem can be used to include dynamic analysis in the solution as technical constraints for the yearly operation. The constraint guarantees a minimum power change response for each block. The proposed model provides the optimal generation expansion plan cost with a reliable operation design considering the power changes in each block. Notice that, considering a maximum power change for each block, all the feasible changes are covered, and as a consequence, the LDC solution is robust for all possible system changes in the planning period for each block. Therefore, the optimal economic power mix problem is solved integrating the ramp velocities in the economic model. A trade-off between the economic and the technical part is created. Finally, the proposed model only solves the one-year problem and it is extended by means of the model predictive control (MPC). The solution of the problem in a prediction horizon provides a new optimal solution that considers the predicted changes in the variables. This methodology is easily improved by including additional constraints and models into the problem.

2.1. Load Duration Curve Discretization. The LDC curve is a continuously decreasing function $D(\alpha_n)$ that represents the amount of time that a certain electricity demand is requested to the power system (see Figure 1). In this section, a LDC discretization is proposed, based on [10, 11]. The proposed LDC discretization minimizes the difference between the $D(\alpha_n)$ area and the area composed by several b_j blocks based on temporal decomposition. As shown in Figure 1, using the time axis with α_n values as optimization variables, the width of each discretized block $\theta_n = \alpha_n - \alpha_{n-1}$ corresponds to the time duration of the block along one year. Analogously, the height of each b_j block represents the maximum required power (or installed capacity) and is given by the $D(\alpha_n)$ function. Now, with θ_j and $D(\alpha_n)$ already defined, the approximation of $D(\alpha_n)$, as a discrete function considering

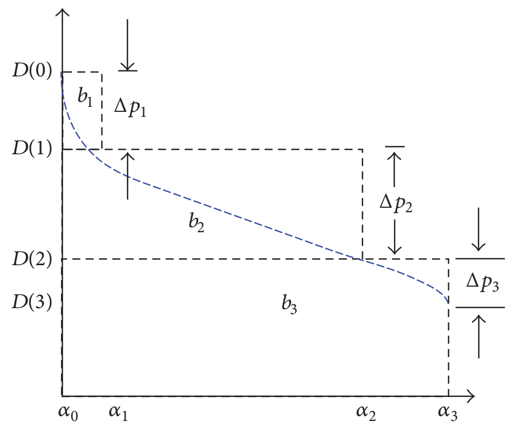

Figure 1: Graphic explanation.

that n is a finite number, $n \in \mathbb{R}^1$ and $n \geq 1$, will have an error associated ϵ that can be expressed as

$$\epsilon = \int_0^{\alpha_n} D(\alpha_n)\,\mathrm{d}\alpha_n - \sum_{n=1}^{\alpha_n} \theta_n D_{\alpha_{n-1}}. \quad (1)$$

If $\int_0^{\alpha_n} D(\alpha_n)\mathrm{d}\alpha_n$ function is approximated piecewise with trapezoids, the accuracy is improved and the result preserves the LDC decreasing characteristic. Hence, it is possible to say that

$$\theta_{\alpha_n} D(\alpha_{n-1}) \geq \theta_{\alpha_n} \frac{D(\alpha_{n-1}) - D(\alpha_n)}{2}. \quad (2)$$

With the described trapezoidal approximation, the named LDC block discretization will always be greater than the LDC function for a finite number of blocks. This provides a confidence interval to generate a maximum amount of energy. The next step minimizes the approximation error between the trapezoid LDC approximation and the energy blocks. If α_n are the mesh points for the time discretization and $N = 1, 2, \ldots, 8760$ the hours of the year, then, it is possible to define the θ_j intervals in hours [h] as optimization variable. Now, with the LDC function, the power value for the α_j point $D(\alpha_n)$ is obtained. In consequence, the product between θ_j and $D(\alpha_{n-1})$ will produce block b_j that represents the energy required by the country along the year. The optimization problem is formulated as follows:

$$\begin{aligned} \min_{\alpha_n} \quad & \left[\sum_{n=1}^{N} (\alpha_n - \alpha_{n-1}) D(\alpha_{n-1}) - \sum_{n=1}^{N} \left(\frac{D(\alpha_{n-1}) - D(\alpha_n)}{2}\right)(\alpha_n - \alpha_{n-1})\right] \\ \text{subject to} \quad & 0 \leq \alpha_n \leq 8760 \\ & D'(\alpha_n) \leq 0. \end{aligned} \quad (3)$$

Using the optimal values that minimizes the LDC discretization error, for simplicity, the optimal trapezoids will be named as energy blocks and represented as follows:

$$\begin{aligned} \theta_j &= \alpha_n - \alpha_{n-1} \\ b_j &= \theta_j D(\alpha_n). \end{aligned} \quad (4)$$

This work considers three blocks to discretize the LDC function $j = 1, 2, 3$. The optimal discrete LDC approach presents the following characteristics for each block: block b_3 has the lowest variation and the minor approximation error. From the financial and operative point of view, this block represents the load related to forward energy agreements. This energy has a small volatility and is dispatched with base load generation technologies. Block b_2 represents an increasing variable energy consumption; this block includes load composed by energy agreements, residential customers, and companies. The volatility of this block is bigger than b_3 block and is correlated with the consumption patterns of regulated users. Also b_2 block energy demand is usually generated with technologies which had affordable prices for big amounts of energy but also should be flexible and with a fast response to the load variations. Finally, the b_1 demand block represents the higher demand points. In one year, these peak demand points have a duration of no more than one hour, and their appearances during the day are few. These low frequency peaks create a flexibility market opportunity; peak demand points imply the need to have a corresponding generation installed capacity available, even if it is only used few hours in the year. It is a duty from the generator and the energy retailers to have the required energy available at any time. In this sense, demand response and load shift among other smart grid technologies can be used to supply the required energy at peak hours; for now, this work wants to deal only with installed capacity to supply the energy.

2.2. Ramping Constraint Model. The discretization proposed in Section 2.1 allows including particular constraints for each block. Particularly, it is possible to find the optimal economic mix of generation technologies including technical constraints of the generation portfolio. The proposed management strategy optimizes the generation technologies mix according to the ramp velocities criteria to meet the power changes values on each block. Considering the notion that every change in the load implies a change in the generation system is true that $\Delta D(\alpha_n) = \Delta p$ results in a change in the operational point of one or several power plants of the system to meet the demand denoted as Δy. Then, it is possible to establish that $\Delta p = \Delta y$ for each t. The generation technology or mix must be able to reach the new operation point in a proper time. Considering a power generation matrix with N_t generation technologies available, it is possible to meet the

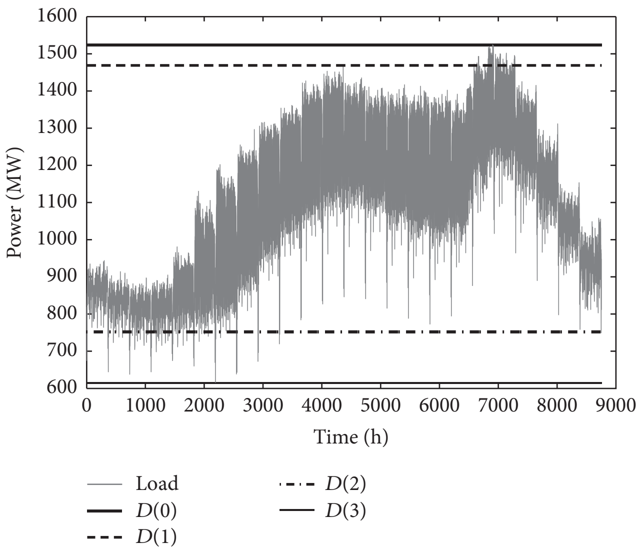

FIGURE 2: Discretization levels and time series match.

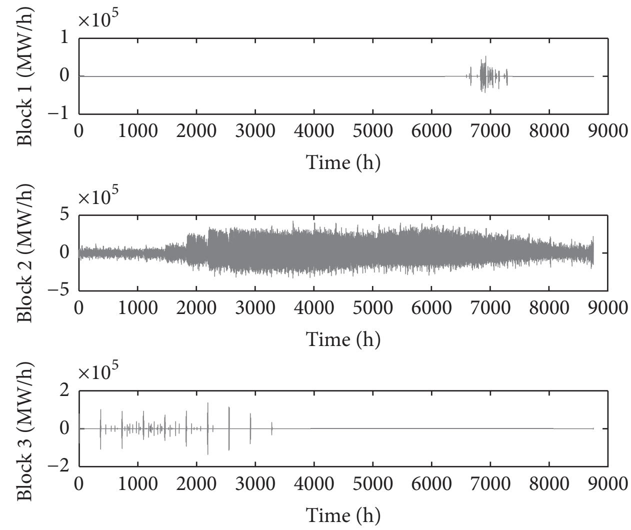

FIGURE 3: Matched block derivatives.

operation changes in the system with a mix of the capacities of each technology represented as a weighted sum, where λ_i is the participation of the ith technology in the power change and V_i is the ramp rate of each technology:

$$\sum_{i=1}^{N_t} \lambda_i V_i y_i = \Delta p. \tag{5}$$

Defining y_i as the produced energy for a generation technology, the variable is correlated with the generation cost and installed capacity. The weighted portfolio approach formulated can be included according to a particular design parameter in the GEP changing the obtained solution. Now, this work will use the load time series analysis described in Section 2.3 to find the Δ_p values for N_b demand levels. These values will be used as the minimum ramping value that the solution must guarantee as follows:

$$\sum_{i=1}^{N_t} \sum_{j=1}^{N_b} \lambda_{ij} V_i \geq \Delta p_j. \tag{6}$$

2.3. Methodology Used for Time Series Analysis and Description of the Data Used. In order to identify the Δ_p value in each demand level as measurement of the higher energy changes in each block, the methodology calculates the time ahead demand time series derivative. To do this, the time series is matched with each demand level obtained in Section 2.1 (see Figure 2). The derivatives of each block are shown in Figure 3. Finally, the Δp_j values are obtained from the maximum derivative value for each block and presented in Table 1. The comparison between the identified and the maximum Δp_j values for each demand level is shown in Table 1. The maximum values represent the biggest change defined by the block size. The data used is described in Section 5.

TABLE 1: Δp_j values for each block.

	Max Δp_j [MW/h]	Derivative Δp_j [MW/h]
Block 1	62	53
Block 2	716	422
Block 3	136	136

3. Ramping Constrained Model Approach

With the Δp_j values of each demand block, the next step is to find the optimal combination of generation technologies to supply the demand at the lowest cost taking into account the ramping constraints. The formulation presented in (6) allows combining the technologies ramp velocities by means of the λ_{ij} values to guarantee a desired performance for each demand block. The integration is made balancing the generation per block of each generation technology y_{ij} with the λ_{ij} values. The $\sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij}\lambda_{ij}\theta_j = b_j$ equality guarantees the installed capacity of each block. The dynamic constraint $\sum_{i=1}^{Nt} \sum_{j=1}^{Nb} \lambda_{ij} V_i \leq \Delta p_j$ puts the desired operative level for the ramping combination in each block. Finally, considering $0 \leq y_{ij} \leq x_i \lambda_{ij}$ the operation of each plant and the installed capacity are also restricted by the λ_{ij} variables; this constraint joint with $\sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij} \leq x_i$ extends the λ_{ij} impact to the installed capacity. The reference for the used variables is presented in Table 2 and the classic and dynamic formulations are presented in (9). To solve the optimization problems, let

$$X = \left[x_1 \ \cdots \ x_i \ \ y_{11} \ \cdots \ y_{1j} \ \cdots \ y_{ij} \ \ \lambda_{ij}\right]^T, \tag{7}$$

where X represents the system variables: installed capacity, use of each technology, and the weights of the dynamic solution for each technology.

$$C = \left[c_1 \ \cdots \ c_i \ \ f_1\theta_1 \ \cdots \ f_1\theta_j \ \cdots \ f_i\theta_j \ \ 0_{ij}\right], \tag{8}$$

Table 2: Variable description.

Variable	Name	Unit
$i = 1, \ldots, Nt$	Generation technologies	
$j = 1, \ldots, Nb$	Discretized blocks	
c_i	Annualized installation cost	[\$/kW]
f_i	Operation cost	[\$/MW]
x_i	Installed capacity	[MW]
y_{ij}	Technology use	[MW]
θ_j	Block duration	[h]
b_j	Maximum required energy	[MWh]
Δp_j	Maximum power change	[MW/h]
λ_{ij}	Velocity weight	[%]

where C is the vector with the generation technologies fixed and variable cost per year. The c_i values represent the annualized installation capacity and fixed operation cost for each generation technology; f_i represent the sum of the operation and maintenance (O&M) cost and the fuel cost for each technology. The use of the annualized costs shares the installed capacity price over the lifespan of each technology. Notice that the cost of the λ_{ij} values is zero. In order to compare the classic and the ramping constrained models, the same cost function is used.

$$
\begin{aligned}
&\text{Economical solution} \\
&\qquad \min_{x_i, y_{ij}} \quad CX \\
&\qquad \text{Subject to:} \quad \sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij} \leq x_i \\
&\qquad\qquad \sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij} \theta_j = b_j \\
&\qquad\qquad 0 \leq x_i \leq \infty \\
&\qquad\qquad 0 \leq y_{ij} \leq \infty \\
&\text{Ramping constrained solution} \\
&\qquad \min_{x_i, y_{ij}} \quad CX \\
&\qquad \text{Subject to:} \quad \sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij} \leq x_i \\
&\qquad\qquad \sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij} \lambda_{ij} \theta_j = b_j \\
&\qquad\qquad \sum_{i=1}^{Nt} \sum_{j=1}^{Nb} \lambda_{ij} V_i \geq \Delta p_j \\
&\qquad\qquad 0 \leq y_{ij} \leq x_i \lambda_{ij} \\
&\qquad\qquad 0 \leq \lambda_{ij} \leq 1
\end{aligned}
\tag{9}
$$

4. Model Predictive Control

The solution of the generation investment planning in a prediction time window is relevant as mentioned in [5]. Here, the merit order dispatch is discussed in front of the emergent dynamic constrains of the power system. The inclusion of variables such as green generation technologies, demand response plans, fuel prices, and storage technologies among others variables becomes necessary to deal with the future scenarios of the power system. The integration of these new variables increases the amount and complexity of the models used in the power system planning and operation. Control applications and control based management strategies had proven their efficiency to achieve good and desired performance in several dynamic and complex systems. The dynamic constrained generation expansion problem formulated in Section 2 found an optimal economic point that meets the imposed LDC dynamics for a single year. The new challenge is to propose an analog dynamic problem formulation that considers the future scenarios and the previous installed capacities in a set of optimal solutions. A well-known tool used to solve constrained dynamic linear and nonlinear problems providing the optimal trajectory for based on the future problem states is the model predictive control (MPC); using the receding horizon principle after the computation of the optimal control sequence applies only the first control actions; then, the next iteration solution provides a new control sequence including the new information available and the previous system states. The loop continues until a desired horizon is reached. This kind of solution provides a planning tool able to analyze several scenarios at the same time, providing a set of optimal trajectories for the variables and control actions that allow analyzing and determining, for each time, the generation system evolution and his related returns including fixed and variable cost.

4.1. Model Predictive Controller Formulation. To create an optimal generation planning tool, this work implements an MPC controller. MPC makes use of the receding horizon strategy that allow solving the ramping constrained model in a prediction horizon. The solution calculates the optimal decisions for the GEP considering future LDC values. Using the model proposed in (9) as an economical objective function and including the proper constraints, the optimal solution formulation is presented considering a time discrete state space model:

$$
\begin{aligned}
x(k+1) &= Ax(k) + Bu(k) \\
y(k) &= Cx(\mathrm{k}) + Du(k),
\end{aligned}
\tag{10}
$$

where $x(k) \in \mathbb{R}^{n_x}$ are the system states, $y(k) \in \mathbb{R}^{n_y}$ are the system outputs, and $u(k) \in \mathbb{R}^{n_u}$ is the current control vector. Using (6), the state space representation of the problem for $i = 1, \ldots, N_t$ generation technologies and a LDC discretized in $j = 1, \ldots, N_b$ blocks can be written as follows:

$$
x(k) = \begin{bmatrix} x_1 & \cdots & x_i & y_{11} & \cdots & y_{ij} & \lambda_{11} & \cdots & \lambda_{ij} \end{bmatrix}^T. \tag{11}
$$

As mentioned, infrastructure investments have a natural condition for the x_i variables: they cannot decrease. Negative changes in the installed capacity would mean a "destruction" or dismantling of the plant; this in the real operation implies to shut down the plant or decrements in the plant efficiency. In this work, negative values are not considered, plant aging is reduced by considering the maintenance cost in the fixed operation cost. However, the aging parameter can be easily included in the space state model.

$$u(k) = \begin{bmatrix} u_{x1} & \cdots & u_{xi} & u_{y11} & \cdots & u_{yij} & u_{\lambda 11} & \cdots & u_{\lambda ij} \end{bmatrix}^T, \tag{12}$$

where $u(k)$ vector represents the control actions taken to modify the x_i variables; u_{xi} represent the decisions taken to increase the installed capacity; u_{yij} represent the expected use of the generations technologies; and $u_{\lambda ij}$ represent the weights of the generation technologies according to the ramp velocities. The interactions between the $x(k)$ and the $u(k)$ variables are described by A and B matrices as follows:

$$A = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & \ddots & 0 & \cdots & 0 \\ 0 & 0 & 1_i & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}, \tag{13}$$

where A represents the states evolution. Thus, the installed capacities are the only variables considered persistent in the system (integration variables). The installed capacity at step $k+1$ depends only on the previous state k and the $u(k+1)$ control actions explicit in the B matrix. $B \in \Re^{n_x \times n_x}$ is an identity matrix. The B matrix indicates the relationship between the decision variables and the state variables. In this case, there is only a direct influence of each control variable over its corresponding state.

$$C = \begin{bmatrix} c_1 & \cdots & c_i & f_1\theta_1 & \cdots & f_1\theta_j & \cdots & f_i\theta_j & 0_{ij} \end{bmatrix}. \tag{14}$$

The C vector is the same as described in (8); the use of the same cost vector in all optimizations cost functions allows directly comparing the results of the presented methodologies. The relationships related to the constraints are explicit in the MPC as hard constraints. Changes in the model output as a consequence of the control actions are not considered; therefore $D = 0$. Now, with the dynamic state space system written, the traditional economic MPC problem based in [12] is defined as follows:

$$\begin{aligned} \min_{u_k} \quad & J_{\mathrm{eco}}(x_k, u_k) \\ \text{subject to:} \quad & x(k+1) = Ax(k) + Bu(k) \\ & y(k) = Cx(k) + Du(k) \\ & x(k) \in \mathbb{X}, \quad k = 0, \dots, N_p \\ & u(k) \in \mathbb{U}, \quad k = 0, \dots, N_p. \end{aligned} \tag{15}$$

At time step k, let $x_k = [x^T(k), \dots, x^T(k+N_p)]^T$ and $u_k = [u^T(k), \dots, u^T(k+N_p)]^T$ be the state trajectory and the control sequences, with N_p being the prediction horizon and $J_{\mathrm{eco}}(x_k, u_k)$ being the economic stage cost. The system is subject to hard constraints on state $x(k) \in \mathbb{X}$, output $y(k) \in \mathbb{Y}$, and input $u(k) \in \mathbb{U}$ for all $k \geq 0$, where $\mathbb{X} \subset \mathbb{R}^{n_x}$, $\mathbb{Y} \subset \mathbb{R}^{n_y}$, and $\mathbb{U} \subset \mathbb{R}^{n_u}$ are closed sets. The objective functions of (9) are clearly a linear combination of the states. Using the MPC methodology, a great flexibility in the objective function is available. In order to calculate the optimal control solution u_k, the cost function will be based on the state space output $y(k) = Cx(k)$ described in (10) as $\widetilde{C}(k) = [C(k), \dots, C(k+N_p)]^T$ and the economic MPC formulation is given by

$$\begin{aligned} J_{\mathrm{eco}}(x_k, u_k) = {} & \sum_{n=0}^{N_p} \widetilde{C}(k+n)\, x_k(k+n) \\ \text{subject to:} \quad & x(k+1) = Ax(k) + Bu(k) \\ & y(k) = Cx(k) + Du(k) \\ & \sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij}(k+n) \leq x_i(k+n) \\ & \sum_{i=1}^{Nt} \sum_{j=1}^{Nb} y_{ij}(k+n)\, \lambda_{ij}(k+n)\, \theta_j \\ & \quad = b_j(k+n) \\ & \sum_{i=1}^{Nt} \sum_{j=1}^{Nb} \lambda_{ij}(k+n)\, V_i \geq \Delta p_j(k+n) \\ & 0 \leq y_{ij}(k+n) \leq x_i(k+n)\, \lambda_{ij}(k+n) \\ & 0 \leq \lambda_{ij}(k+n) \leq 1. \end{aligned} \tag{16}$$

5. Case Study

As an application case, the 2013 year demand data from EPM (Empresas Publicas de Medellin) that is one of the biggest energy retailers from the center region of Colombia sharing the 23.9% of the maximum 25% allowed by the country regulation is used. The demand is composed by regulated and nonregulated users; in Colombia, there are not differential energy prices, and even regulated costumers ignore the real-time energy price. Therefore, the regulated load does not have an energy saving culture making use of the energy at any time along the day increasing the load volatility. Renewable generation technologies are not mature in the market, neither are demand response or similar technologies. The generation technologies used in the problem are selected considering competitive technologies in terms of cost and ramping rates into the problem; the technical values are obtained from [8, 13] and presented in Table 3. The results compare the traditional economical LDC solution without ramping constraints and the ramping constrained LDC methodology described in Section 2.1. Three additional artificial scenarios shown in Figure 4 are created based on the data set. The first scenario is taken from the demand time series presented in Figure 3 and

Table 3: Generation technologies cost and operational variables.

Gen. tech.	Capital cost [$/kW]	Fixed cost [$/kW]	Variable cost [$/MWh]	Life [years]	Ramp rate [MW/h]
Coal	1700	34	36	40	240
OCGT	486	12	76	20	600
CCGT	855	21	53	30	360

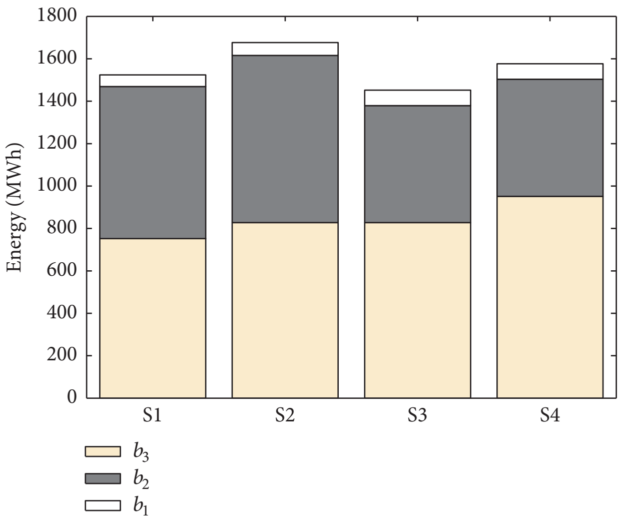

Figure 4: LDC scenarios.

the demand levels obtained from the discretization presented in Section 2.1. The Δ_p values of the first scenario correspond to the values presented in Table 1. The remaining scenarios are hypothetical and they are designed to stress the methodology in front of positive and negative LDC and dynamics changes as follows: second scenario presents a 10% growth in all the blocks for the b_j and Δ_p values assuming a positive development in the country. The third scenario assumes an additional 10% increase in block 1 and a 30% reduction in block 2. Finally, the fourth scenario simulates a 10% growth in block 3 load.

5.1. Economic and Ramping Constrained Comparison. The installed capacities for each solution are presented in Figure 5 and the generation mix use for each scenario is presented in Figures 6 and 7; the traditional model without ramping constraints and the proposed ramping constrained model provides the same solution for the first scenario: a base load technology operating in blocks b_2 and b_3 with higher energy demand. An OCGT (open-cycle gas turbine) generation plant is the choice in the b_1 block providing the energy with a higher cost but the lowest install capacity cost (see Figures 5 and 6). In this solution, the same technology mix meets the ramping requirements. Then, in scenario number two, the absence of ramping constrains increases the installed capacity mix of scenario 1 proportionally to the increase of each demand level. The lack of ramping constraints makes the solution blind to the dynamic changes of the demand. In contrast, a noticeable change in the generation mix is made by the ramping constrained solution compensating the demand increment using CCGT (combined-cycle gas turbine) in the solution. This change increases the cost but represents the lowest cost possible to meet the ramping requirements. The trade-off between capacity and the response flexibility of the system has been shown. Scenario three presents a particular case where the classic and the ramping constraint solutions are the same. The derivative value in this scenario is included in the feasible region where the classic solution has his optimal value. Scenario three shows that, in relaxed cases where the dynamics are not so severe (low load values), the classic and the ramping constrained solutions could be the same. Finally, scenario four shows how a increment in the base load can move the optimal point increasing the coal installed capacity and generating the energy in all the blocks only with the cheapest technology. The result generates an interesting solution where a big installed capacity of a slow generation technology could meet the imposed load dynamics.

5.2. Model Predictive Control Results. The use of MPC as generation investment planning tool results are presented. As designed in A matrix, the MPC should keep the installed capacity between scenarios and increases the values if it is needed. Comparing the installed capacity of the ramping constrained solution with the MPC results in Figure 8, the previous capacity values are preserved. When a previous installed capacity is already built, the optimization has the choice to turn off a particular technology and to pay the fixed O&M cost and supply the energy with another technology. The second scenario as seen in Section 5.1 pushes the system to another technology mix including CCGT as base generation plant increasing the energy production cost. The MPC keeps the previous coal capacity of scenario one and installs a small CCGT installed capacity amount to fulfill the problem requirements. This behavior creates the opportunity to include and manage demand response technologies designed to supply small amounts of energy with low installation cost. Scenarios three and four present smaller load values. The MPC keeps the previously installed capacities avoiding the negative changes presented in Figure 5.

With the installed capacities described in Figure 8, the MPC proposes a different energy generation mix for each scenario presented in Figure 9. Now, having the installed capacities and fixed O&M cost, stabilized generation costs are the key to achieve the economic optimal. The dynamic imposed to the installed capacity allows deciding, in the planning horizon, which technology is the most appropriated to work in a specific scenario selecting which plants should be turned on or off. The strategy offers a planning tool making use of the cheapest technology efficiently and covers high load dynamics with fastest but expensive technologies.

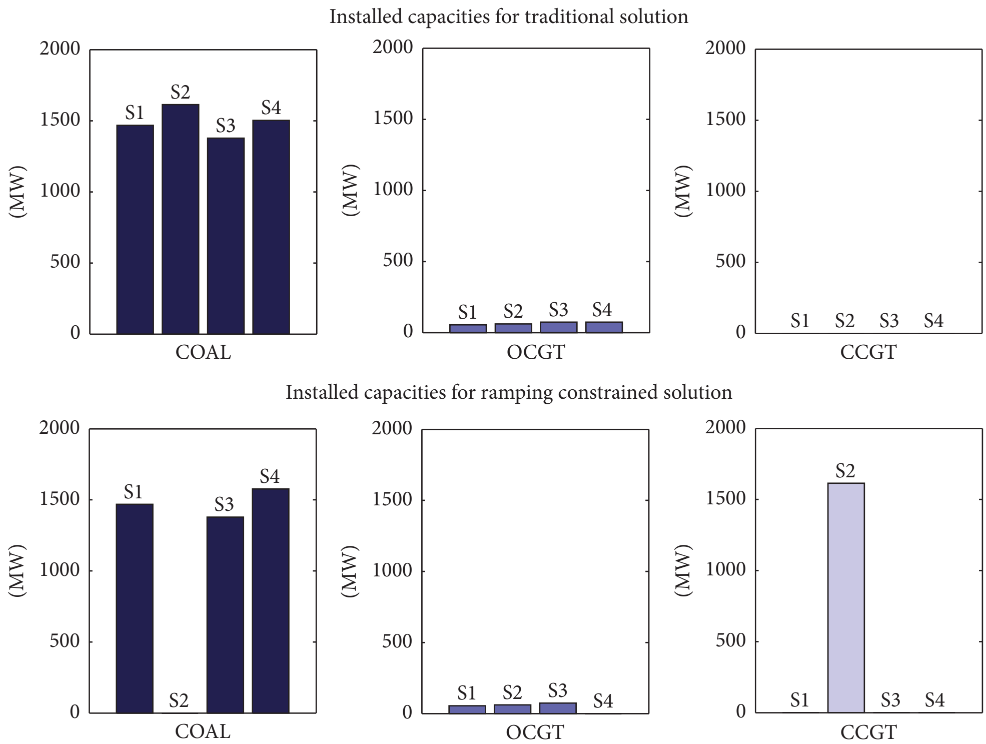

Figure 5: Traditional and ramping constrained installed capacities for each scenario.

Table 4: Economic cost comparison of the solutions.

	S1	S2	S3	S4
Traditional	5.75e + 08	6.33e + 08	5.41e + 08	5.9e + 08
Ramping	5.75e + 08	7.83e + 08	5.41e + 08	5.94e + 08
MPC	5.75e + 08	6.44e + 08	5.53e + 08	5.92e + 08

Finally, the economic cost presented solutions are compared in Table 4. The presented values correspond to the objective function of each solution. As expected, the traditional solution is always the cheapest solution. The ramping constraint increased the solution cost in scenarios two and four where the load and ramping condition increased. Finally, the MPC faced the scenarios keeping the solution cost close to the traditional solution but at the same time meeting the solution cost. Finally, the MPC solution minimizes the economic overall cost meeting the ramping constrains and staying close to the traditional methodology cost.

6. Conclusions

The above presented work proposed an optimal generation planning tool based on a modified GEP. The GEP is improved including a technical constraint that considers the generation technologies ramp velocities and the load dynamics in the optimization. The constraint includes the ramping values of the generation technologies and mix them to satisfy a design operating condition optimizing to the lowest cost of the installed capacity and fixed and variable values cost of the generation portfolio. Then, using MPC theory, the optimal long-term planning problem is solved providing a new generation mix that is reliable in front of load dynamics and keeps a minimal economic cost. The LDC discretization used in the GEP is improved minimizing the difference between the LDC and three demand levels. As a result, generated levels are used to classify the load time series dynamics and also represent the expected energy required by each level per year. This representation resumes the load and the demand peaks per year with a few values allowing the easy integration of several data sources as stochastic models, expert knowledge, or even fictional scenarios. This provides a planning tool useful to analyze several cases with low computational time. Presented discretization is not suitable for real-time operation due to the assumption of the ramp values in MW/h, when they usually are given in orders of MW/min. Last, solving the proposed ramping constrained model and comparing the solution with the exclusive economic model applied to four scenarios, a comparison of the performance is made. The comparison shows that considering the generation technology ramp velocities in the technology mix problem defines a new optimal solution cost. The new solution provides a reliable generation mix design able to fulfill the system power changes imposed by the load

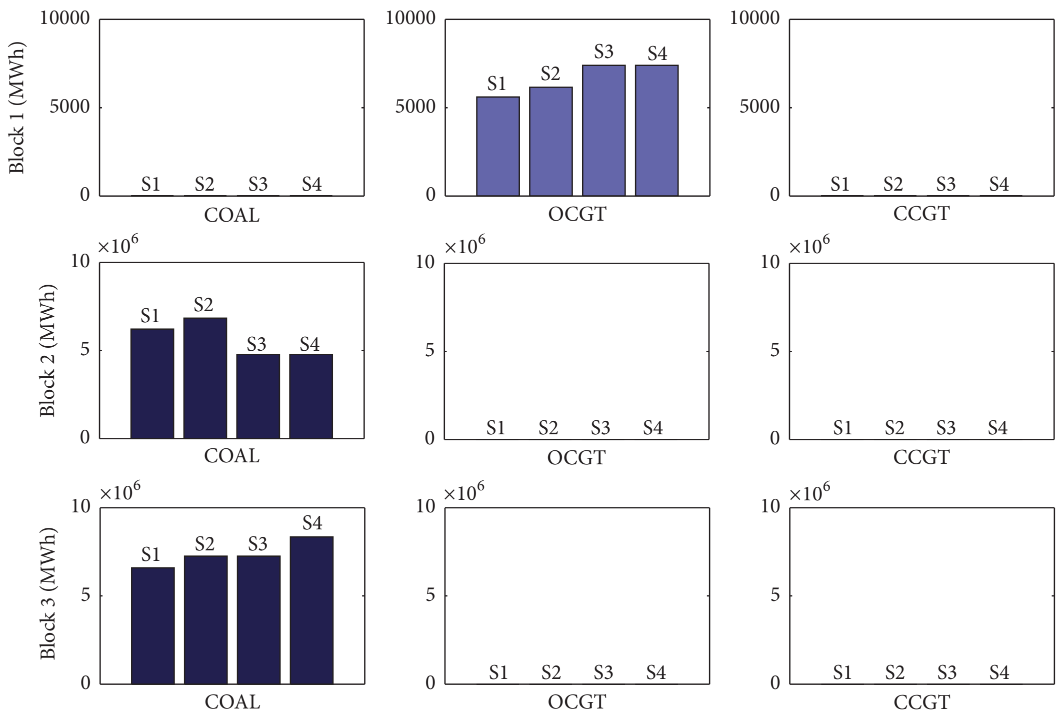

Figure 6: Traditional solution use for each scenario.

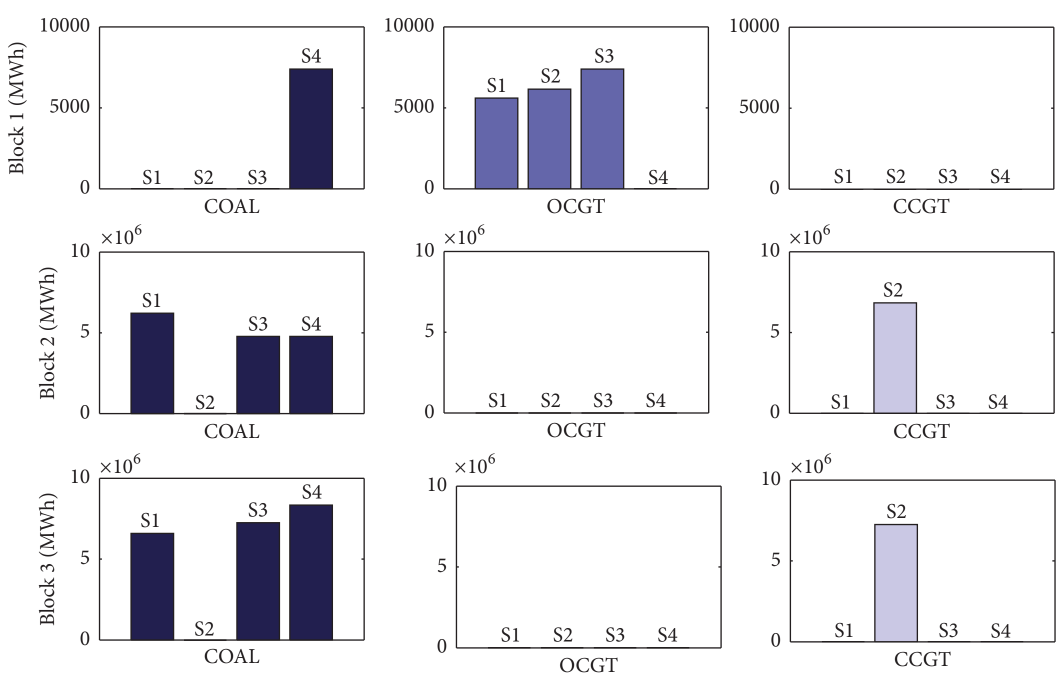

Figure 7: Ramping constrained solution use for each scenario.

dynamics. Then, using the MPC methodology, the model is used to create an optimal generation investment plan. The MPC formulation provides a vector with the optimal solutions for all the scenarios in the order of seconds. The methodology deals with the uncertainties of the LDC forecast considering past and future values of the variables to make an technical and economical GEP solution. The MPC strategy found an optimal economic solution including the ramping constraints into the problem. Mixing the operation of slow and fast generation technologies, the strategy minimized the installed capacity changes, meeting the load requirements by keeping the economic cost close to the traditional solution.

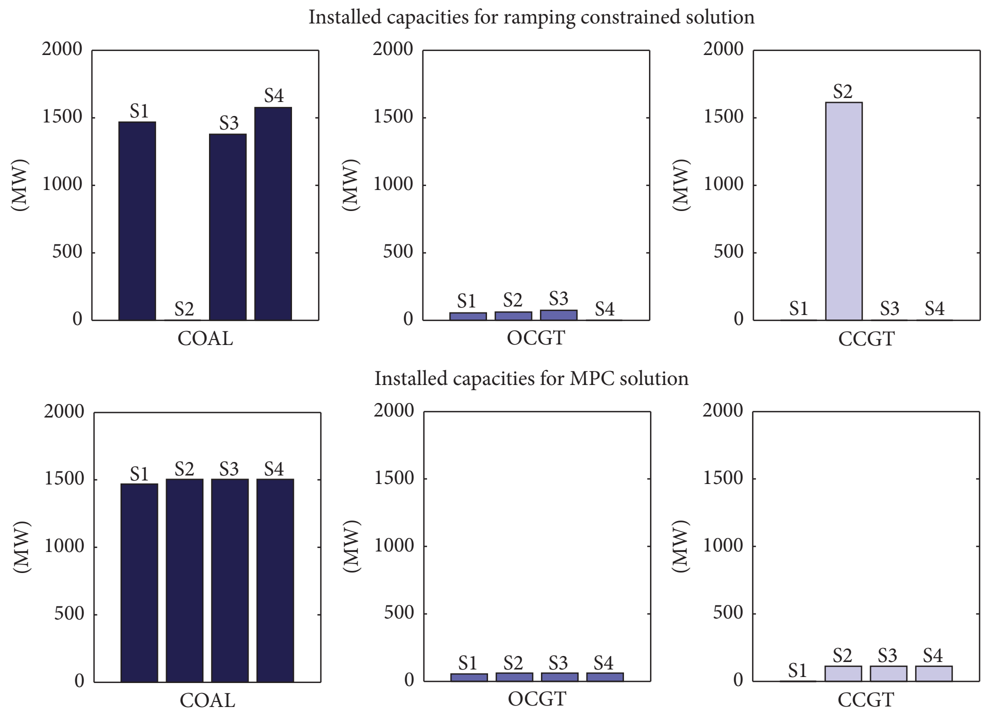

FIGURE 8: MPC solution: installed capacity for each scenario.

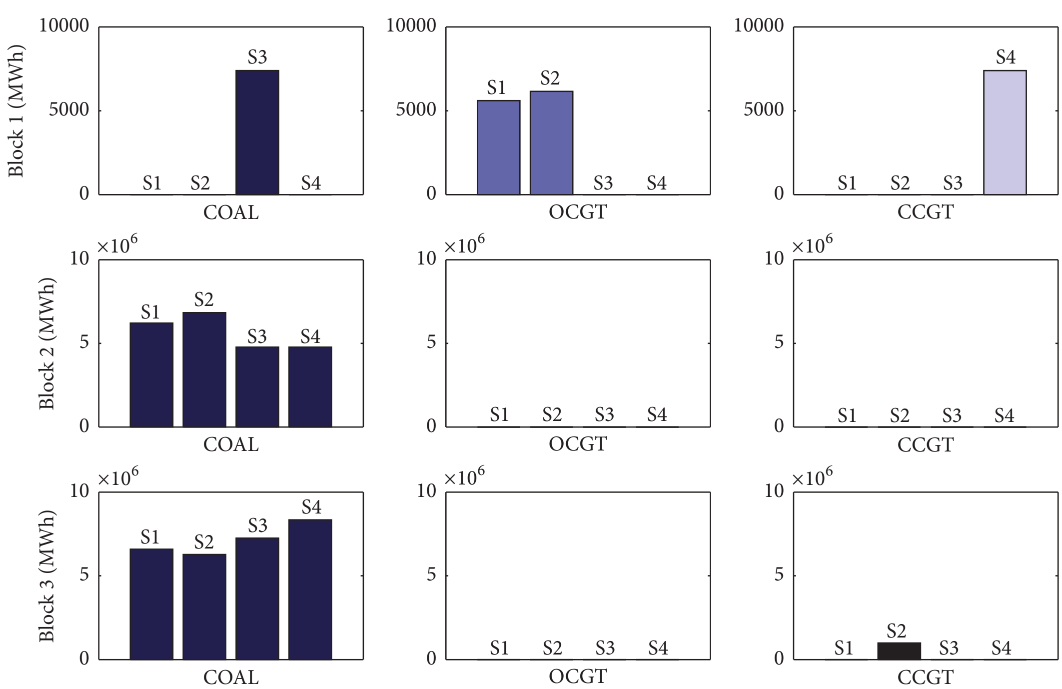

FIGURE 9: MPC solution use for each scenario.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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