Optimal Generation Mix With Short-Term Demand Response and Wind Penetration

Cedric De Jonghe, Benjamin F. Hobbs, *Fellow, IEEE*, and Ronnie Belmans, *Fellow, IEEE*

***Abstract*—Demand response, defined as the ability of load to respond to short-term variations in electricity prices, plays an increasingly important role in balancing short-term supply and demand, especially during peak periods and in dealing with fluctuations in renewable energy supplies. However, demand response has not been included in standard models for defining the optimal generation technology mix. Three different methodologies are proposed to integrate short-term responsiveness into a generation technology mix optimization model considering operational constraints. Elasticities are included to adjust the demand profile in response to price changes, including cross-price elasticities that account for load shifts among hours. As energy efficiency programs also influence the load profile, interactions of efficiency investments and demand response are also modeled. Comparison of model results for a single year optimization with and without demand response shows peak reduction and valley filling effects, impacting the optimal amounts and mix of generation capacity. Increasing demand elasticity also increases the installed amount of wind capacity, suggesting that demand response yields environmental benefits by facilitating integration of renewable energy.**

***Index Terms*—Demand response, energy efficiency, generation technology mix, load management, wind power generation.**

NOMENCLATURE

$A_j, B_{j,k}$	Parameters of inverse short-term demand response function after simplification.
C	Total system costs.
cap_i	Optimal generation capacity.
DEM_j	Fixed (perfectly inelastic) demand level.
D_j	Short-term demand response function.
d_j	Demand level corresponding to function D_j.
EE	Energy efficiency expenditures.
EE_0	Reference energy efficiency expenditures.
ε_j	Own price elasticities.
$\varepsilon_{j,k}$	Cross price elasticities.
FC_i	Fixed investment costs.
$g_{i,j}$	Generation output level.
i	Index for generation technologies.
j	Index for hours.
P_0	Quantity weighted average reference price.
P_{0j}	Hourly energy price with demand DEM_j.
P_j	Inverse short-term demand response function.
p_j	Equilibrium price corresponding to function $\mathrm{P_j}$.
VC_i	Variable investment costs.
$\mu_{i,j}$	Dual variable of capacity constraint.
γ_j	Elasticity of demand with respect to energy efficiency expenditure.
δ_j	Efficiency-price cross elasticity of demand.

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C. De Jonghe and R. Belmans are with the research group Electa (ESAT), Katholieke Universiteit Leuven, Kasteelpark Arenberg 10, 3001 Heverlee, Belgium (e-mail: Cedric.DeJonghe@esat.kuleuven.be; Ronnie.Belmans@esat.kuleuven.be).

B. F. Hobbs is with the Johns Hopkins University, Baltimore, MD 21218 USA (e-mail: bhobbs@jhu.edu).

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I. INTRODUCTION

LARGE-SCALE wind power development affects short-term operation of the electricity system, as well as the optimal generation technology mix. In operations, wind significantly increases the variability of generation. Fluctuations in the amount of wind power fed into the grid require compensating changes in the output of flexible generators. As flexibility of conventional generation technologies is restricted by technical constraints, such as ramp rates, the increasing need for flexible generators should be considered when defining the optimal generation technology mix.

Demand response can be another source of this needed flexibility. Integration of smart grid technologies in the power system creates opportunities to more efficiently balance supply and demand. In 1988, Schweppe [1] proposed real-time pricing to incent consumers to modify their loads in response to system conditions, for example trimming peak loads or shifting them to off-peak periods. Although Schweppe's vision has gone largely unfulfilled, interest in demand response has grown recently in part because such response can also help power systems adapt to short-term variations in renewable energy supplies [2]. Unfortunately, a lack of real-time billing has prevented most consumers from seeing and responding to real-time prices, resulting in inelastic demand in short-term

[3]. Consequently, traditional models have disregarded demand response, suggesting the optimal generation technology mix given projected load levels, and neglecting the potential for short-term demand elasticity to trim peak loads and manage renewable energy fluctuations. But because demand response will be increasingly important in the future, these models need to be enhanced in two ways. First, dynamic operating constraints should be included, in order to value the flexibility contributed by both new demand- and supply-side resources in the face of increased penetration of renewables. Second, the representation of demand should include own- and cross-price elasticities, respectively allowing consumers to adjust consumption or shift it in time.

This paper is organized as follows. First, in Section II, we review how models can define the optimal generation technology mix. Then in Section III, three methods are suggested to integrate the short-term demand response into a linear programming (LP)-based model. This model represents generator operating flexibility by including chronologic dispatch constraints. The model is also extended to account for investments in energy efficiency, and their potential impact on the amount of demand response. Results of an example application are presented in Section IV, followed by conclusions in Section V.

II. Literature Review

The LP formulation of the investment and operating cost minimization problem was first presented in [4] and offers solutions relevant to a regulated market or central planning context. These models define the optimal type, timing, and, in some cases, location of new plants, considering a time horizon of 20 years or more [5].

The basic model formulation has been extended in the past two decades to include variables and constraints that account for the following features: optimal plant scheduling, system security, installed reserve margins [6], and regulatory constraints such as emissions caps. Resource attributes such as must-run capacity, operating reserve capabilities, and requirements for periodic maintenance [7] can also be added.

Although LP models have been successful because of their ability to model large problems, mixed integer programming must be used when binary variables are associated with investment projects or non-convexities, such as minimum run levels and minimum up- and downtimes.

Stochasticity has also been incorporated, accounting for random plant outages and uncertain scenarios concerning economic and technology drivers [8]. By adding uncertainties (standard deviations) and correlations of different cost components, optimal risk-cost portfolios can be found [9].

In general, the above-mentioned investment models undertake a sophisticated supply-side analysis while greatly simplifying the demand-side. Demand distributions are typically described by a load duration curve, constructed by sorting load in order of decreasing hourly values, or an approximation based on discrete load steps [8]. This representation loses information about critical low and high load situations, as well as chronologic hourly variability. Load chronology was disregarded under the assumption, held for many years, that interperiod operating constraints are unimportant to investment decision making. However, this assumption is no longer tenable when there is a large amount of variable energy.

In the 1970s, the energy crisis triggered public awareness of the potential benefits of energy conservation, and utilities recognized that demand-side options could be seen as an alternative for satisfying customers' demand. The challenge in the 1980s for the utilities was to integrate the concept of influencing demand into traditional planning models [10]. The paradigm of integrated resource planning (IRP) resulted [11]. Energy efficiency is the most widely pursued type of demand-side management (DSM) [10], while peak clipping programs were also important. These programs can be driven by utility or governmental DSM subsidies, or result simply from consumers responding to higher average prices by making investments in equipment that reduces consumption. Such investments can be viewed as a long-term demand response to average price levels.

A few early IRP models included this long-term price response [12], without considering how consumers might respond in the short-term to hourly varying prices. This was valid as long as consumers did not see spot prices, which used to be the case. However, as demand response programs become more common, this assumption is no longer valid. A more sophisticated example of this type of model considered the time lag or response gap until the next invoice period, resulting in medium-term consumption adjustments [13]. More recently, economists have considered the benefits of enabling consumers to see and react to short-term prices. The impact of varying the share of customers who respond to short-term prices is explored in [14]. Long-term efficiency gains from implementing demand response along with real-time tariff structures are calculated in [14] and some degree of demand elasticity is included in [15]. A supply function equilibrium approach is used in [16] to model oligopolistic competition in a capacity expansion model, in an elaboration of the more traditional approach of assuming perfect competition. Special attention is paid to electricity prices and the resulting optimal installed generation capacities.

However, these papers treat generation in simplified manner, disregarding short-term operational and interperiod constraints. Further, none of the above models considered how DSM programs interact with demand response; by decreasing overall loads, aggressive efficiency programs may lower the extent to which consumers can adjust consumption in response to short-term price variations.

This review of the literature indicates that there have been no generation technology mix models that simultaneously integrate energy efficiency programs, demand response to hourly varying prices, and dynamic operating constraints. In the next section, we propose such a model.

III. Model Description

A. Basic Model With Operational Constraints

First we describe a basic cost minimization model that excludes demand response. This cost minimization model can be viewed as either or both of the following situations:

- a simulation of a perfectly competitive market in which all market parties are price-takers, and demand in hour j (DEM_j) is fixed (perfectly inelastic); in this case, the decision makers are individual generation companies who react to the market prices.
- an optimization model for a vertically integrated utility.

The model is a static, single node LP model; extensions to include transmission and multiple years are straight forward, although they increase problem size [6], [8]. On the one hand, a static optimization allows us to address the question of optimal generation technology mix, exploring the effects of including a large share of variable renewable power generation and an elastic demand-side. In an actual planning problem, multiple years over a planning horizon would be considered in a fully dynamic model; there is no obstacle to doing so. Such a model would consider an existing fleet of plants as well decommissioning of older generation plants. It could also help illustrate how a transition toward more renewables and simultaneously a more responsive demand-side would occur. A multiple year optimization would also allow consideration of the technology-specific lead time for construction.

The cost minimization objective function is subject to a system energy balance constraint (supply in each hour equals demand), as well as capacity and operational constraints. With a fixed demand profile, the model pursues the reduction of system costs (C), including fixed (FC_i) and variable (VC_i) costs for each technology i. The installed generation capacity (cap_i) and generation output $(g_{i,j})$ in hour j are decision variables, respectively representing the optimal investment decisions and plant scheduling.[1] The system cost minimization instantaneously satisfies the system energy balance requirement and is subject to constraints among which chronological constraints that account for the need for operational flexibility.

The application considers four thermal generation technologies. Consideration of more types of generation technologies would be appropriate in a real study. However, since broad technology classes are considered, no fundamentally different insights would be obtained. Therefore, in the interest of simplicity and transparency, the number of generation options considered has been limited. Wind power is modeled as an hourly profile (% of capacity), multiplied by a decision variable representing installed capacity (MW). Hourly variability is incorporated, assuming perfectly predictable output. Energy storage, using a pumped hydro facility, can be used to ensure the system energy balance. Excess wind power injections can even be curtailed. Generation output is restricted by a must-run constraint for base and mid load generation technologies. Forced outages are handled by derating, a common approach in linear programming and especially in capacity expansion. As an exception, probability production costing models, which account for the effect upon expected generation costs and customer outages of random plant forced outages, have been incorporated into the LP approach by decomposition methods [17], [18]. Also periodic maintenance could be handled by the usual means of derating capacity during months in which such maintenance takes place. Ramping constraints are included, limiting hour-to-hour output changes. Finally, positive and negative balancing requirement constraints are included enforcing upward and downward generation flexibility, respectively. Balancing requirements depend on the amount of projected wind power injections. The full model is presented in [19]; to explain how we include demand response, we use the below simplified version:

$$Min\ C = \sum_i FC_i * cap_i + \sum_{i,j} VC_i * g_{i,j} \tag{1}$$

$$subject\ to:$$

$$\sum_i g_{i,j} = DEM_j \qquad \forall i \in I \tag{2}$$

$$0 \leq g_{i,j} \leq cap_i \qquad \forall i \in I, \quad \forall j \in J. \tag{3}$$

B. Representing Short-Term Demand Response

This subsection illustrates how a short-term demand function with cross-elasticities is constructed, which we then include in the optimal generation technology mix model. To represent short-term demand response, elastic demand functions have to be calibrated for each hour. We express quantity demanded as a function of the energy portion of the retail price (excluding fixed charges, such as transmission and distribution).[2] This is done by defining a reference price and quantity demanded for each hour $\{P_0, DEM_j\}$, and then using elasticity assumptions to fit a demand curve through that price-quantity pair. The reference quantity demanded is based on a load forecast. The reference price is obtained by applying the LP model to the reference demand levels. The reference price (P_0), assumed to be the same in all hours, is the quantity weighted average of the hourly (marginal) energy prices (P_{0j}) over the time horizon [(4), below]. Those hourly marginal energy prices correspond to the dual variable of (2).

In other words, the reference price-quantity pair is the anchor of a linear demand function (Fig. 1). The slope of the function is determined by the price elasticity assumptions, including both own-price elasticities $(\varepsilon_{j,j})$ and cross-price elasticities $(\varepsilon_{j,k})$, with hours k not equal to j. The inclusion of price elasticities yields a short-term demand response function D_j [(5), below] that expresses quantity demanded (d_j) as a function of relative deviations from the reference price level (P_0). Inverting the function D_j gives the inverse demand function P_j (6), ex-

[1]Lumpy investment constraints, utilizing binary variables, are not included. Even though lumpiness better represents reality, because power plants come in discrete and indivisible sizes, binary variables require mixed integer optimization modeling. Mixed integer models are harder to solve, limiting the number of time steps that can be included into the model defining the optimal generation technology mix. Thus, the decision to include binary variables is based on a tradeoff between the need for realistic generator sizes versus the need for more realistic production costing through consideration of more hours. Because our system is relatively large, the impact of disregarding lumpiness constraints is less than it would be for smaller systems.

[2]Price elasticities describe the percent change in quantity demanded in response to a 1% change in retail price. If instead expressed as a function of percent changes in bulk prices, the elasticities are smaller (as a given €/MWh price change would be a higher percentage of bulk prices than of retail prices).

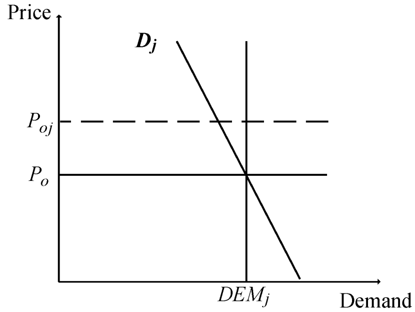

Fig. 1. Construction of a short-term elastic demand function for hour j.

pressing the equilibrium price (p_j). We use this form in our model, with parameters A_j and $B_{j,k}$, after simplification:

$$P_0 = \sum_j P_0 j * DEM_j \tag{4}$$

$$D_j : d_j = DEM_j + \sum_k \varepsilon_{j,k} \frac{DEM_j}{P_0}(p_k - P_0) \tag{5}$$

$$P_j : p_j = P_0 + \sum_k \frac{1}{\varepsilon_{j,k}} \frac{P_0}{DEM_k} \equiv A_j + \sum_k B_{j,k} d_k \tag{6}$$

with parameters :

$$A_j = P_0 - \sum_k \frac{a}{\varepsilon_{j,k}} P_0 \tag{7}$$

$$B_{j,k} = \frac{1}{\varepsilon_{j,k}} \frac{P_0}{DEM_k}. \tag{8}$$

C. *Methods to Include Short-Term Demand Response*

When short-term demand response is integrated into the generation technology mix model, minimization of generation costs does not yield sensible results, because that would disregard the benefits consumers receive from electricity consumption [20].

Three different methods to integrate short-term demand elasticity into an LP investment model are presented below. Except for possible numerical approximation errors, each yields a solution that corresponds with the equilibrium conditions that supply equals consumption and that the marginal value of consumption (price) from the demand function equals the marginal cost of supply in each period (accounting for both marginal investment and operations costs). The demand function is (5); supply marginal cost is instead an implicit function that is calculated by the LP.

We now summarize how demand response is included by the three methods by referring to the simplified version of the basic model [(1)–(3)]. In each method, quantity demanded (d_j) in hour j is now a decision variable, replacing the basic model's fixed demand (DEM_j) in the right side of (2). The first method (complementarity) directly solves a set of mathematical conditions that include the first-order conditions of a version of (1)–(3) whose objective instead maximizes revenue (price times quantity sold) minus cost, together with the inverse demand function (6); together, these form a competitive equilibrium model. The second (quadratic programming, QP) solves a version of (1)–(3) in which the objective function is a total surplus or "pseudo-welfare" function that maximizes the integral of the inverse demand functions minus cost; the first-order conditions of that model are equivalent to the complementarity model. The third approach (PIES algorithm) iteratively solves a version of (1)–(3) in which the objective is a piecewise linear approximation of the pseudo welfare function, refining the approximation in each iteration.

1) Complementarity Programming Method: A first way to include short-term demand response is by a complementarity program model structure, representing a competitive equilibrium in which energy suppliers and consumers maximize their individual profits and consumer surplus, respectively, and the market clears. The complementarity model solves a system of conditions including each market player's first-order optimality (Karush-Kuhn-Tucker, KKT) conditions, plus market clearing (supply = demand) [21]. As this model minimizes the cost of meeting a particular quantity demanded and accounts for demand response to prices, it can be viewed as a model defining the optimal generation technology mix.

More specifically, consider a revised version of the supply model in which (1) is replaced by

$$Profit = PQ - C(Q) = \sum_j P_j \left(\sum_i g_{i,j} \right) - (1) \tag{9}$$

and the only constraint is (3), as (2) is no longer needed. Q refers schematically to quantity supplied. The KKT conditions of the profit maximizing generator (9) for variables $g_{i,j}$ and cap_i are given by (10) and (11), respectively. The capacity constraint (3) of this simplified model is condition (12), with its dual variable given by $\mu_{i,j}$, which is the marginal value of capacity for that plant during that hour. Whenever the capacity of technology i during hour j is binding, its marginal value $\mu_{i,j}$ can be positive. Equation (10) shows that in equilibrium, the hourly energy price p_j equals the sum of the variable generation cost and capacity shadow price for each generating unit. If one of the generation types is basic (i.e., is generating a level strictly between 0 and its capacity), then the price precisely equals its variable cost. Meanwhile, the equilibrium conditions for consumers, one condition per hour j, are given by (14), which is a generalization of (6) that prevents load from becoming negative. Finally, the market clearing condition is (14). The dual associated with the market clearing condition (p_j) is the hourly (marginal) energy price that clears the market. Together, (10)–(14) define a mixed linear complementarity problem (MCP), in which the problem is to find non-negative $(g_{i,j},\ cap_i,\ d_j,\ and\ \mu_{i,j})$ and free (p_j) variables associated with inequality and equality conditions, respectively [22].

Generator KKTs:

$$0 \leq VC_i - p_j + \mu_{i,j} \perp g_{i,j} \geq 0 \quad \forall i \in I, \forall j \in J \tag{10}$$

$$0 \leq FC_i - \sum_j \mu_{i,j} \perp cap_i \geq 0 \quad \forall i \in I \tag{11}$$

$$0 \leq cap_i - g_{i,j} \perp \mu_{i,j} \geq 0 \quad \forall i \in I, \quad \forall j \in J \tag{12}$$

Consumer inverse demand:

$$0 \leq -A_j \sum_k B_{j,k} * d_k + p_j \perp d_j \geq 0 \quad \forall j \in J \tag{13}$$

Market clearing:

$$0 = \sum_i g_{i,j} - d_j, \quad p_j free \quad \forall j \in J. \tag{14}$$

The advantage of this method is that more general instances of the inverse demand function (6) or (13) can be solved, because the matrix of $B_{j,k}$ does not have to be symmetric. The MCP can be solved by standard complementarity solvers such as PATH. A disadvantage of those solvers is the limited size of problems that can be solved, usually an order of magnitude or more smaller than LP solvers. Another disadvantage is that no 0–1 binary variables can be introduced. Such variables are required when modeling investment lumpiness.

2) Quadratic Programming Method: A second way to integrate short-term demand response in the model is QP [23]. Continuous QP models (without binary variables) can be shown to be a subset of MCP models, since the QP's KKT conditions are an MCP [22]. An MCP with short-term demand response (10)–(14) can be reformulated as a QP if demand and/or supply functions are linear and the coefficient matrix $B_{j,k}$ (8) is symmetric. This integrability condition allows construction of an objective function whose derivative is the inverse demand function (6). If this condition is unsatisfied, the model should be solved as an MCP, or it might be possible to construct a symmetric matrix that closely approximates the actual matrix.

The QP problem can be seen as a market equilibrium problem among producers and consumers, each maximizing their surplus. Consistent with Samuelson's principle [24], under our assumptions, this is the same as maximizing total surplus. The resulting QP is as follows:

$$\begin{aligned} &Max\ Total\ Surplus \\ &\quad = \left\{ \sum_j \left[d_j * A_j + \frac{1}{2} d_j \sum_k B_{j,k} d_k \right] \right\} \\ &\qquad - \left\{ \sum_i cap_i * FC_i + \sum_{i,j} g_{i,j} * VCi \right\} \end{aligned} \tag{15}$$

$subject\ to:$

$$\sum_i g_{i,j} - dj = 0 \quad \forall j \in J \tag{16}$$

$$0 \le g_{i,j} \le cap_i \quad \forall i \in I, \forall j \in J. \tag{17}$$

The dual variable to (16) is the market price p_j. Compared to the complementarity method, the QP has the advantage that adding more constraints does not introduce more dual variables into the formulation. Additionally, nonlinear optimization software is widely availability of nonlinear optimization software, whereas MCPs need specialized solvers. However, some NLP solvers may be less robust in finding a global optimum, compared to MCP solvers, but this depends on the problem formulation and NLP solver used. Alternatively, the demand function has to be integrable in a QP problem, which in the linear case means that the matrix of $B_{j,k}$ need to be symmetric ($B_{j,k} = B_{k,j}$), this is not a restriction for the complementarity method. Finally, QPs can include 0–1 binary variables unlike complementarity problems, but QPs also have the disadvantage of limited problem size relative to LP solvers.

3) Piecewise Integration (PIES Algorithm): This method finds the market equilibrium by adding a piecewise linear approximation of the consumer value function to the basic model's objective (1), considering only own-elasticities. The resulting model is a LP. The approximation accounts for the marginal effects of changes in quantity upon that surplus. The LP chooses the optimal hourly demand levels d_j so that the approximation to total surplus is maximized. The effect of non-zero cross-price elasticities is considered by iteratively resolving the LP, in each iteration updating the quantities demanded using (6). This procedure will converge, assuming dominance of own-price elasticities (i.e., own-price elasticities are larger in magnitude than the sum of cross-price elasticities). The dual of (2) equals the energy price, subject to an approximation error.

The methodology is introduced in [25] in the context of national energy models (in particular, the Project Independence Evaluation System, or PIES), while convergence is mathematically proven in [26]. Full details of our application of this methodology to consider short-term demand response when defining the optimal generation technology mix are given in [27].

This equilibrium solution is the same as the one obtained by the MCP and QP methods, as long as own-price elasticities are dominant. Asymmetric (non-integrable) demand functions can be considered, which is not possible in the QP method. Since the PIES method yields an LP, very efficient optimization software is available, and it is able to solve large versions of this modified problem (1)–(3). However, unlike the MCP and QP approaches, it requires the implementation of an iterative solution procedure, which requires more effort in the form of customized computer code as opposed to use of standard optimization packages. Additionally, 0–1 binary variables for unit commitment or new plants can be included, unlike the complementarity method.

D. Impact of Energy Efficiency Programs

Short-term demand response has been integrated into the generation technology mix optimizing model as elastic demand functions, as just explained. An approach to including energy efficiency programs sponsored by government and utilities is suggested in this section. Pursuing energy efficiency reduces hourly electricity consumption, but can also impact the responsiveness of demand. Positive interactions are possible, e.g., when consumers buy efficient appliances with built-in demand response capability [28]. But negative interactions can also occur, e.g., as efficient appliances, when switched off in response to higher prices, yield smaller load reductions [29].

Since energy efficiency programs are increasingly popular, it is desirable to extend the elastic linear demand functions in order to account for interactions with those programs. In our extension, the elastic demand function is simplified to account only for own-price elasticities. Our starting point is to view the linear, hourly demand function D_j (5) as a Taylor series approximation with the second and higher order own partial terms being dropped. However, our representation (18) has a non-zero second-order interaction term that accounts for the interactive effect of energy efficiency expenditures (EE) (in terms of its deviation from a reference level of expenditures EE_0) with short-term prices:

$$D_j(p_j,EE)=D_j(P_{0j},EE_0)+\frac{\partial D_j(P_{0j}),EE_0}{\partial p_j}(p_j-P_{0j}) + \frac{\partial D_j(P_{0j},EE_0)}{\partial EE}(EE-EE_0) + \frac{\partial^2 D_j(P_{0j},EE_0)}{\partial p_j \partial EE}\frac{(p_j-P_{oj})(EE-EE_0)}{2}. \quad (18)$$

The first derivative with respect to price as well as energy efficiency expenditure is negative. The last term, the cross second partial, is used to account for interactive effects. In (19)–(21), we replace the derivatives with expressions that include price elasticity of demand ε_j, elasticity of demand γ_j with respect to efficiency expenditures, and efficiency-price cross elasticity of demand δ_j, accounting for the impact of efficiency expenditures on the responsiveness of demand:

$$\frac{\partial D_j(P_{0j},EE_0)}{\partial p_j} = \varepsilon_j \frac{DEM_j}{P_{oj}} \quad (19)$$

$$\frac{\partial D_j(P_{0j},EE_0)}{\partial EE} = \gamma_j \frac{DEM_j}{EE_0} \quad (20)$$

$$\frac{\partial^2 D_j(P_{0j},EE_0)}{\partial p_j \partial EE} = \varepsilon_j \gamma_j \delta_j \frac{DEM_j}{P_{oj}} \frac{DEM_j}{EE_0}. \quad (21)$$

Substituting these expressions yields the final form of the demand function, including interactions with energy efficiency:

$$D_j(P_j,EE) = D_j(P_{0j},EE_0) + \varepsilon_j \frac{DEM_j}{P_{oj}}(P_{0j}) + \gamma_j \frac{DEM_j}{EE_0}(EE-EE_0) + \varepsilon_j\gamma_j\delta_j \frac{DEM_j}{P_{oj}}\frac{DEM_j}{EE_0} \times \frac{(p_j-P_{oj})(EE-EE_0)}{2}. \quad (22)$$

Finally, (22) can be inverted to yield the inverse demand function that corresponds to (6). This allows (22) to be implemented using any of the three solution approaches. Note that parameter EE could be included as a decision variable in the model (e.g., as discussed in [6]), but for simplicity we treat it here as a decision that is exogenous to the model.

IV. Case Study and Results

A. Data and Assumptions

We take four thermal generation technologies into account, i.e., base, mid, peak, and high peak load. Ordering technologies in terms of decreasing capital cost and increasing operating cost, the first are nuclear and coal units, respectively, whereas peak and high peak load technologies correspond to combined cycle gas turbines (CCGT) and oil- or gas-fired open cycle gas turbines (OCGT). Annualized fixed generation costs in Table I are scaled considering a four-week period (672 h).[3] Ramp rate limits are based upon expert judgment concerning flexibility of the respective technologies. Lower ramp rates are assigned to base and mid load technologies. Less stringent ramp limits are assumed for peak and high peak load generation units [19]. A must-run requirement of 10% of the total installed capacity is included for base and mid load generation technologies.[4] Total installed generation capacity is derated by 10%, defining the available capacity after accounting for periodic maintenance and forced outages. When operating the pumped hydro unit, offering additional flexibility at the supply-side, a storage efficiency of 81% is considered.

TABLE I
Annualized Fixed Generation Costs

Cost category		Base	Mid	Peak	High Peak
Investment	[k€/MW/yr]	195	80	25	15
Fixed O&M	[k€/MW/yr]	65	20	15	10
Fuel	[€/MWh]	10	25	40	62
Variable O&M	[€/MWh]	5	10	10	10

Historical wind power and demand data on an hourly step are used (based on Danish data, http://www.energinet.dk). The wind power time series is multiplied in the model by the amount of wind power capacity, a decision variable. A range of annualized investment costs for wind are considered, ranging from 100 k €/MW/yr up to 140 k €/MW/yr, scaled considering the 672-h period.[5] When the system is in an over-generation situation due to excess wind power energy supply, wind power injections can be curtailed at the cost of 30 €/MWh.[6] Full documentation of the data is found in [19].

Price elasticities of demand are likely to vary across hours and there is no obstacle to including them into the model. However, in the absence of data on this variation and in the interest of simplicity of presentation in this illustrative application, elasticities are assumed to be time-invariant. In this analysis, own-price elasticities of demand of −0.10 and −0.20 are tested. These numbers are comparable to data in [30] and [31], after rescaling for transmission, distribution, and customer account charges. We also consider a range of cross-price elasticities, with aggregated magnitudes of 0.08 or 0.16 over the previous and subsequent 4 h to ensure symmetry. Only a limited period of load shifting is considered, assuming that consumers shift loads over relatively short few hours. However,

[3]Annualized investment costs require discount rate assumptions. Those costs are calculated using a 10% discount rate. Different discount rates may be used by GENCOs in their decision making, depending on their financial situation and their business strategy [37].

[4]Although this is a low requirement on a per unit basis, it is nevertheless realistic when the total installed capacity represents several units. In that case, with some units being turned off, the 10% must-run requirement for total capacity would correspond to a higher per unit requirement for the capacity which is still on.

[5]The three investment cost levels, 100, 120, and 140 k €/MW/yr and the resulting wind power installed capacities can be interpreted as a high, medium, and low wind power integration scenarios, respectively.

[6]A cost minimizing generator, operating in a perfectly competitive market, faces an opportunity cost when curtailing wind power if subsidies, such as tradable green certificates, are paid per MWh of wind power generation.

TABLE II
OPTIMAL GENERATION TECHNOLOGY CAPACITY: REFERENCE SCENARIO [MW]

Wind Cost Scenario	Base	Mid	Peak	High Peak	Wind	Total
100 k€/MW/yr	2,092	2,161	1,579	1,358	4,341	11,531
120 k€/MW/yr	3,434	1,567	1,437	1,002	2,188	9,628
140 k€/MW/yr	4,051	1,573	1,594	697	319	8,233

our approach can incorporate other assumptions, such as load shifting over a longer timeframe or from day to night. Data about cross-price elasticities over time periods longer than 4 h are given in [32], whereas demand elasticities within and between morning, mid-day, evening, and economy periods are discussed in [33].[7] The formulation assumes that consumers have foreknowledge of hourly prices and reschedule their loads earlier as well as later to avoid high prices. The coefficient matrix is adjusted slightly to ensure that the integrability condition is satisfied, so the QP method can be used. We solved versions of the model with symmetric demand functions by all three methods; their results were the same, as anticipated.

As mentioned above, we express expenditures for energy efficiency EE as a percentage of current expenditures EE_0. A 0% as well as 50% increased level of expenditures are considered in separate runs, and both -0.05 and -0.10 values of the efficiency elasticity parameter γ_j are considered. In order to account for interactions between demand response and energy efficiency, a 0.0025 and 0.005 efficiency-price cross elasticity of demand δ_j has been assumed as interaction term in (22).

B. Reference Scenario

First, the optimal generation technology mix is calculated for a reference scenario without real-time demand response. The optimal capacity levels are shown in Table II for different levels of wind investment costs. Unsurprisingly, the lowest wind investment cost assumption (100 k €/MW/yr) incents the most installed wind capacity. By subtracting wind power generation from initial load levels, a net demand profile is found, illustrated by the "no response" line in Fig. 2. Wind power curtailment is allowed in order to eliminate excess injections during high wind periods, e.g., around hour 27. Consequently, the price would have plunged to the curtailment cost of -30 €/MWh at that time.

The impact of ramping constraints in the model without short-term demand response is discussed in [19]. Table II shows that in the highest wind penetration case, base load technologies are strongly reduced. One possible reason for this is that the levelized cost of wind power (38 €/MWh at an average capacity factor of 30%) is less than the levelized cost of base load plants (48 €/MWh, at a capacity factor of 90%). However, levelized cost comparisons may be misleading for comparing intermittent and dispatchable generating technologies because they fail to take into account differences in the production profiles of intermittent and dispatchable generating technologies. Typically, levelized cost comparisons overvalue intermittent generating technologies compared to dispatchable base load generating technologies [34]. Another explanation is evident in the partial replacement of base load capacity with mid load generation technologies. This is because the latter offers more flexibility to deal with the high variability of net demand. Demand valleys, corresponding to low net demand levels, also reduce the number of operating hours of base load plants. Therefore, it is optimal to replace base load by mid load generation technologies, having a lower required number of operating hours. Additionally, the high variability of net demand also yields a larger installed capacity of high peak generation technologies. Finally, the total installed generation capacity increases when there is more wind capacity installed, due to its relatively low average capacity factor.

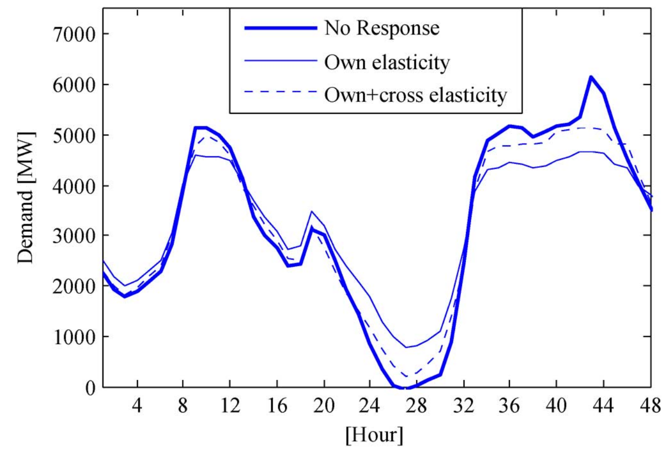

Fig. 2. Net demand: -0.20 own/$+0.16$ cross-elasticity (100 k €/MW/yr).

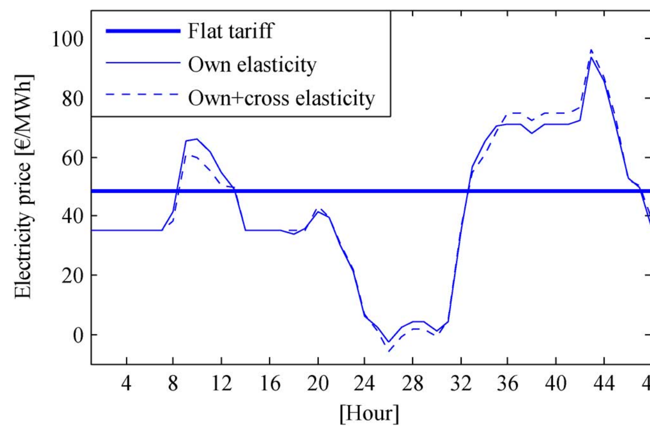

Fig. 3. Price comparison: -0.20 own/$+0.16$ cross-elasticity (100 k €/MW/yr).

C. Impact of Demand Elasticity

Typically, lower and higher net demand levels result in lower and higher electricity prices, respectively. The MWh weighted average price level for the reference case is calculated and shown as "flat tariff" in Fig. 3. When consumers are able to adjust their consumption in response to real-time price signals, demand levels are increased during low demand hours (valley filling), and reduced during peaks (peak shaving).

The effect of including own- and cross-price elasticities on net demand levels and electricity prices, compared to the reference case (no response and flat tariff), is illustrated in Figs. 2 and

[7] Including positive cross-price elasticities over a longer timeframe counteracts negative own-price elasticities in the respective hour. In order to prevent from those negative modeling elements, and for illustrative purposes, only a 4 period timeframe is considered.

TABLE III
PRICE ELASTICITY SENSITIVITY ANALYSIS

Scenario	Base	Mid	Peak	High Peak	Wind	Total
Own-price elasticity -0.10						
100 k€/MW/yr	2,175	2,051	1,148	449	4,666	10,489
120 k€/MW/yr	3,633	1,369	903	277	2,317	8,499
140 k€/MW/yr	4,338	1,396	1,148	17	118	7,016
Own-price elasticity -0.20						
100 k€/MW/yr	2,237	1,973	729	446	4,935	10,321
120 k€/MW/yr	3,816	1,220	506	259	2,403	8,203
140 k€/MW/yr	4,545	1,256	702	17	124	6,643
Own-price elasticity -0.20 / cross-price elasticity 0.08						
100 k€/MW/yr	2,210	2,020	963	445	4,768	10,405
120 k€/MW/yr	3,697	1,303	744	268	2,360	8,373
140 k€/MW/yr	4,412	1,335	973	20	148	6,887
Own-price elasticity -0.20 / cross-price elasticity 0.16						
100 k€/MW/yr	2,169	2,078	1,285	448	4,549	10,529
120 k€/MW/yr	3,572	1,379	1,070	283	2,337	8,641
140 k€/MW/yr	4,280	1,418	1,281	23	153	7,156

3, respectively. For clarity reasons only 48 h out of the 672-h period optimization are shown. These 672 h are treated as a sample of the 8760 h per year, so the results for these periods are extrapolated to annual results by multiplying the resulting short-term costs by 8760/672.

During peak demands, e.g., hour 43, price spikes can be seen. When real-time prices rise above the flat tariff, price-responsive consumers reduce their demands (compare the thick continuous lines); the reverse happens during low price periods. Additionally, the complex effects of cross-price elasticity (dashed line) become apparent. Most of the time, consumer demand response is weakened with the dashed line lying between the "no response" and "own elasticity" case. At other times, cross elasticities yield a different demand response. The former situation occurs when the price in hour j as well as in previous and subsequent hours is above the flat tariff. The latter situation would occur when the price in hour j is lower than the flat tariff and the price in previous and subsequent hours is higher than the flat tariff.

Peak demand reductions are consistent with values found in literature. Based on [30], peak reductions from demand response as large as 26% can be expected. Actual peak demand reductions between 8.5% and 18.5% are documented in [35] for a range of customer types. Further, during off-peak periods, minor demand increases were observed in those studies.

A sensitivity analysis of the effect of demand elasticity upon installed capacity is summarized in Table III. First, most remarkable is the reduction of the installed high peak capacity when including price responsive consumers, compared to Table II. Demand response often clears the market during peak periods, reducing peak demands and the need for such capacity. With an own-price elasticity of -0.10 and no cross-price effects, the installed high peak capacity falls by a factor of 3 to as low as 449 MW in the lowest wind power investment cost scenario. In contrast, without demand response, more than 1300 MW was required. Second, demand response increases the optimal base

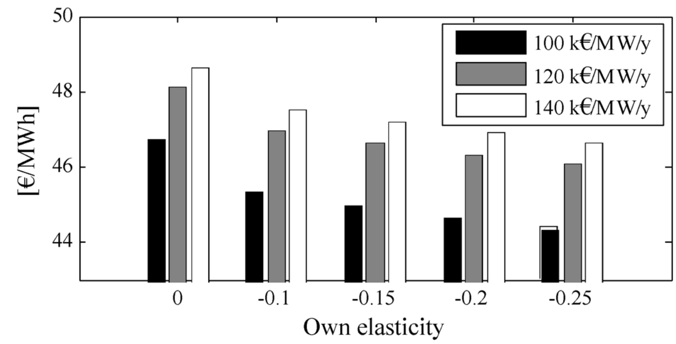

Fig. 4. Weighted average electricity price impact.

load capacity between 5% and 10%,. The variability of the net demand is reduced and valley filling effect increase the number of operating hours base load generation technologies can have. Third, higher price elasticities yield more installed wind power capacity, especially for the lowest wind power investment cost scenario. The optimal wind capacity can increase by 7% given -0.10 own-price elasticity and by up to more than 13% given -0.20 own-price elasticity. This shows that demand response can significantly contribute to integration of variable renewable energy generation.

Finally, for a given level of own-price elasticity, increasing cross-price elasticity reduces the above-mentioned effects because now a price increase in hour j results not only in a load decrease in that hour, but some compensating load increases in earlier and later hours. When several consecutive hours have similar prices, this means that the net effect of higher prices is less than if only own-elasticities are under consideration. A reduced net effect of price reduces demand flexibility. Consequently, increasing the cross-price elasticity reduces the optimal installed wind power capacity and yields again larger high peak generation capacities, compared to the scenario without cross-price elasticities.

The impact of demand elasticity on the weighted average bulk electricity price is shown in Fig. 4, excluding transmission and distribution charges. The reference price level for different wind power investment costs corresponds to the "0 own elasticity" scenario. Consumers facing real-time prices are encouraged to consume more during low price hours and less during high price hours. Consequently, the weighted average price decreases by up to 2 €/MWh.

D. Impact of Energy Efficiency

First, the sensitivity of load to efficiency investments influences the optimal generation mix. Table IV shows the optimal generation mix for different levels of efficiency elasticity of demand (γ_j). In this analysis, a -0.20 own-price elasticity of demand is assumed with zero cross-price elasticities, and the energy efficiency program budget is assumed to be increased by 50%. Considering just the first-order effect of efficiency expenditures on loads, we assume a -0.05 and -0.10 elasticity for the effect of efficiency expenditures upon demand. Then if the budget for energy efficiency is increased by 50%, this elasticity causes a reduction in demand of 2.5% and 5% on average for each wind case, yielding demand reductions of 100 to 150

TABLE IV
ENERGY EFFICIENCY IMPACT: 50% BUDGET INCREASE/−0.20 OWN-ELASTICITY

Scenario	Base	Mid	Peak	High peak	Wind	Total
Efficiency elasticity -0.05						
100 k€/MW/yr	2,189	1,914	693	436	4,825	10,056
120 k€/MW/yr	3,735	1,176	473	253	2,347	7,984
140 k€/MW/yr	4,448	1,211	664	16	120	6,458
Efficiency elasticity -0.10						
100 k€/MW/yr	2,139	1,857	656	422	4,716	9,790
120 k€/MW/yr	3,653	1,131	443	246	2,293	7,765
140 k€/MW/yr	4,351	1,165	626	15	116	6,274
Efficiency elasticity -0.05 / efficiency-price cross elasticity 0.0025						
100 k€/MW/yr	2,123	1,981	1,000	446	4,708	10,258
120 k€/MW/yr	3,656	1,227	791	268	2,291	8,233
140 k€/MW/yr	4,353	1,258	1,027	17	122	6,777
Efficiency elasticity -0.05 / efficiency-price cross elasticity 0.005						
100 k€/MW/yr	2,080	2,015	1,435	574	4,574	10,678
120 k€/MW/yr	3,553	1,290	1,307	331	2,290	8,771
140 k€/MW/yr	4,244	1,320	1,512	73	157	7,306

MW and 200 to 300 MW, respectively. As a result, less conventional and renewable generation capacity is needed. The total installed capacity is reduced from 11 531 MW to 9790 MW in the low wind investment cost scenario, comparing Table III with Table IV.

Second, energy efficiency expenditures and demand response can significantly interact. This interaction is captured by δ_j. This parameter reduces the responsiveness of demand when more is spent on energy efficiency. Because this impact of efficiency expenditures upon price elasticities has only been discussed qualitatively [28], we arbitrarily assume a value of δ_j of 0.0025 and 0.005. In the latter case, given −0.20 own-price elasticity and a 50% price increase with a demand of 7000 MW, initial demand levels are reduced by 700 MW. The interaction with 50% increased efficiency expenditures dampens the initial demand reduction almost by half. With increased energy efficiency expenditures, the optimal amount of wind capacity is reduced. Comparing Table III with Table IV shows that the optimal wind power capacity is also reduced by about 100 and 200 MW with 50% additional and −0.05 and −0.10 efficiency elasticity, respectively (given 100 k €/MW/yr investment cost and −0.20 own-price elasticity). When including a δ_j of 0.005, the resulting reduction in short-term demand responsiveness results in a lower optimal installed wind power capacity of 4708 MW and a larger high peak generation capacity. This shows that considering interactions between energy efficiency and price elasticity can significantly affect optimal generation mixes.

Fig. 5 shows the load impact of demand response combined with energy efficiency expenditures, compared with the original, no response load profile. The original load profile is indicated by the bold full line. With an own-price elasticity of −0.20, assumed in Fig. 5, peak demand is reduced around hours 9 and 43, and some valley filing occurs circa hour 27.

Additionally, if energy efficiency expenditures are increased by 50% (efficiency elasticity −0.05), demand levels are slightly reduced. This is indicated by the dashed line just below the thin full line. If an interaction is assumed between the effects of demand response and energy efficiency (efficiency-price cross elasticity 0.005), the responsiveness of demand is reduced. Consequently, peak load reduction and valley filling are noticeably less pronounced than without this counteracting effect (as indicated by the dashed line in the figure).

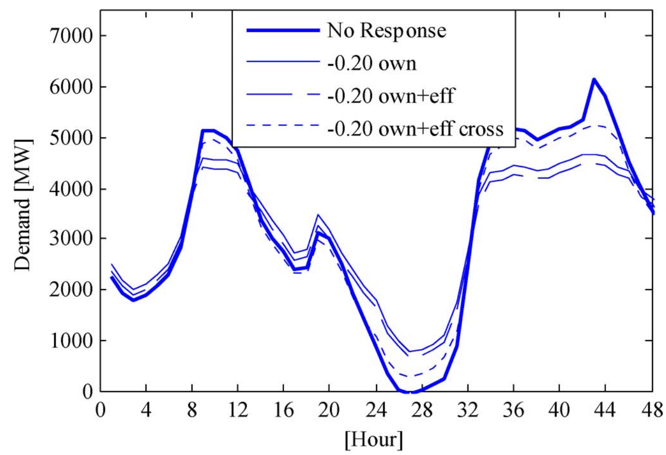

Fig. 5. Demand response impacts under alternative elasticity assumptions.

V. CONCLUSION

Since the 1950s, generation investment decision making has been supported by LP-based models. Here, these models are extended to incorporate two considerations that are increasingly important as more wind energy enters the generation mix. These include operational constraints that limit the flexibility of thermal generators and short-term response of consumers to spot electricity prices.

Elastic demand functions for these models are built based on historic hourly demand levels and assumed levels of elasticities. These include own-price elasticity as well as cross-price elasticities with respect to prices in other hours in order to capture load shifting effects. A typical LP-based cost-minimization investment model is expanded to account for demand response. Three numerical approaches to accomplish this supply-demand integration are presented. In addition, the interactions of energy efficiency investments and demand responsiveness are also modeled by including those investments as first- and second-order terms in the demand function.

The integration of demand response dampens system peaks, decreasing the required investment in peaking generation capacity. Additionally, demand response creates valley filling effects, lessening over-generation problems during the night or high wind generation periods. Demand response also increases system flexibility, facilitating integration of variable wind power. Simulations show that for higher demand elasticity, it becomes optimal to install a higher amount of wind capacity. These methods can be applied in a cost benefit analysis [36].

By increasing consumption during low price hours and decrease consumption during high price hours, demand response reduces the weighted average electricity price. However, including cross-price elasticities reduces these effects as consumption during high price periods is shifted to other hours instead of being indefinitely postponed.

Finally, the impact of energy efficiency is analyzed. Of course, such investments reduce loads and therefore the required installed generation capacity. This benefit is reduced when the negative interaction of energy efficiency investments upon the short-term responsiveness of demand is considered. This interaction affects the power generation mix and the optimal amount of installed wind power capacity is reduced.

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Cedric De Jonghe received the M.S. degree in business engineering in 2007 from the K.U.Leuven, Leuven, Belgium, where he currently is pursuing the Ph.D. degree.

Since 2007, he has been working as a Research Assistant at K.U.Leuven. He is a member of the Electa Branch of the K.U.Leuven Energy Institute. From May until July, he was a visiting researcher at the Electricity Policy Research Group (University of Cambridge, Cambridge, U.K.). His fields of interest include demand-side modeling and wind power integration.

Benjamin F. Hobbs (SM'01–F'08) received the Ph.D. degree in environmental systems engineering from Cornell University, Ithaca, NY.

He is Schad Professor of Environmental Management in the Department of Geography & Environmental Engineering, Johns Hopkins University, Baltimore, MD, and directs the JHU Environment, Energy, Sustainability & Health Institute. In 2009–2010, he was on leave at the Electricity Policy Research Group, University of Cambridge, Cambridge, U.K..

Dr. Hobbs is a member of the California ISO Market Surveillance Committee.

Ronnie Belmans (S'77–M'84–SM'89–F'05) received the M.S. degree in electrical engineering in 1979 and the Ph.D. degree in 1984, both from the K.U.Leuven, Leuven, Belgium, a Special Doctorate in 1989 and the Habilitierung in 1993, both from the RWTH, Aachen, Germany.

Currently, he is a Full Professor at the K.U.Leuven, teaching electric power and energy systems. His research interests include techno-economic aspects of power systems, power quality, and distributed generation. He is also a Guest Professor at Imperial College, London, U.K. From June 2002 until May 2010, he was Chairman of the Board of Directors of ELIA, the Belgian transmission grid operator.