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Evaluation of a rapid LMP-based approach for calculating marginal unit emissions

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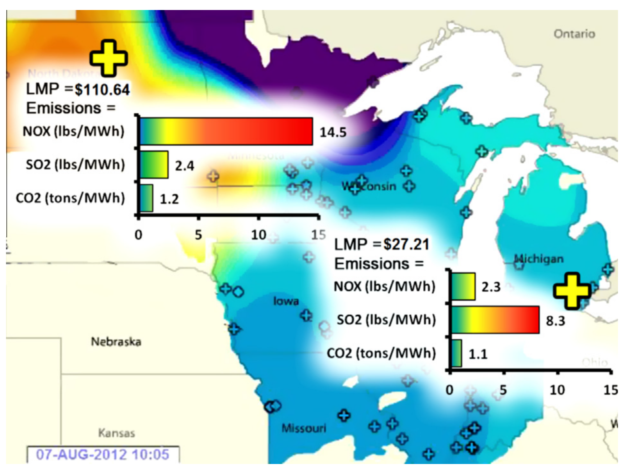
HIGHLIGHTS

- Pollutant emissions estimated based on locational marginal price and eGRID data.
- Stochastic model using IEEE RTS-96 system used to evaluate LMP approach.
- Incorporating membership function enhanced reliability of pollutant estimate.
- Error in pollutant estimate typically <20% for CO_2 and <40% for NO_X and SO_2.

GRAPHICAL ABSTRACT



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ABSTRACT

To evaluate the sustainability of systems that draw power from electrical grids there is a need to rapidly and accurately quantify pollutant emissions associated with power generation. Air emissions resulting from electricity generation vary widely among power plants based on the types of fuel consumed, the efficiency of the plant, and the type of pollution control systems in service. To address this need, methods for estimating real-time air emissions from power generation based on locational marginal prices (LMPs) have been developed. Based on LMPs the type of the marginal generating unit can be identified and pollutant emissions are estimated. While conceptually demonstrated, this LMP approach has not been rigorously tested. The purpose of this paper is to (1) improve the LMP method for predicting pollutant emissions and (2) evaluate the reliability of this technique through power system simulations. Previous LMP methods were expanded to include marginal emissions estimates using an LMP Emissions Estimation Method (LEEM). The accuracy of emission estimates was further improved by incorporating a probability distribution function that characterize generator fuel costs and a membership function (MF) capable of accounting for multiple marginal generation units. Emission estimates were compared to those predicted from power flow simulations. The improved LEEM was found to predict the marginal generation type approximately 70% of the time based on typical system conditions (e.g. loads and fuel

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costs) without the use of a MF. With the addition of a MF, the LEEM was found to provide emission estimates with errors typically less than 25% for CO_2, and less than 50% for SO_2 and NO_X. Overall, the LEEM presented provides a means of incorporating pollutant emissions into demand side decisions.

Nomenclature

C_i	cost of generation for generator i (\$/MW h)
F_i	(\$/MMBtu) fuel price of generator i
CO_2	carbon dioxide
ef_i	emission factor for generator i
eGRID	US EPA's Emissions & Generation Resource Integrated Database
ER_i	emission rate of a specific pollutant from plant i
f_i	degree of membership for generator i
ISO	independent system operator
lb	pounds
k_{i2}, k_{i1} and k_{i0}	polynomial coefficients used to model the heat rate
LEEM	LMP emission estimation method
LME	locational marginal emission
LMP	locational marginal price
MATS	Mercury and Air Toxics Standards
MF	membership function
MISO	Midwest Independent System Operator
MMBtu	million metric British thermal units
MW h	megawatt hour
N_{bus}	total bus number
NG_i	net generation at plant i
NO_X	nitrogen oxides
p_i	power output (MW) of generator i
PDF	probability distribution function
RFCM	Reliability First Corporation Michigan
RTO	transmission organizations
SO_2	sulfur dioxide
μ	mean
σ	standard deviation
P_i	active power output of generator i
H_i	average heat rate of a plant (MMBtu/MW h)

1. Introduction

Electric power generation is a major source of air pollution. In 2010, power plants were responsible for 64% of SO_2 emissions, 16% of NO_X emissions, 40% of CO_2 emissions, and 68% of mercury air emissions in the US [1]. In the US power generation and energy demand are coordinated through regional energy markets managed by regional transmission organizations (RTOs) and independent system operators (ISOs). Because each ISO functions differently the amount of information that is made available to the public varies. Annual air pollutant loads from electrical generation are well documented for all regions due to reporting requirements by the US Environmental Protection Agency (EPA) and Energy Information Administration (EIA). However, real-time and spatially accurate information describing emissions is not easily obtained. This lack of transparency hinders the ability to make control decisions based on the amount of emissions that would be generated at any time. To quantify changes in emissions due to real-time demand controls, a model has been developed to estimate changes in pollutant emissions based on locational marginal prices (LMPs) [2]. While the original method provided a theoretical construct for estimating pollutant loads that could be used to drive demand-side decisions it (1) lacked regional specificity regarding pollutant emission factors, (2) was unable to account for more than one marginal unit, and (3) has yet to be validated. The purpose of this paper is to enhance the LMP Emission Estimation Method (LEEM) by addressing the first two short comings and verify its effectiveness.

LMPs are the wholesale electricity prices used by most RTOs and ISOs to efficiently manage the electric transmission system [3]. LMPs are locational, because they are published for thousands of node locations, and marginal because they represent the price for the next incremental unit of load at a particular time and place [4,5]. In other words, LMPs represent the cost to generate and deliver the next MWh of electricity [6] and take into account three things: the cost of generation, transmission constraints, and system losses [2]. If system losses are negligible, then LMP is a function of system constraints and the cost of generation. A constraint occurs when a physical limitation(s) of the transmission network is reached, making the transmission of electricity from the cheapest source to the demand inefficient or impossible. In these locations differences in LMPs will be observed across the line constraint and, as a result, different marginal units can be observed across the line constraint.

LEEM utilizes the LMP to identify the pollutant emission profile (i.e. emission factors) of a marginal generator, based on fuel type, for a given location and time [2]. The use of LMPs to estimate air emissions is powerful, because near real-time LMPs are publically available for many locations [7]. If real-time estimates for air emissions were made widely available, it may be possible to shift demand (spatially and temporally) to reduce air emissions due to power generation. This is particularly true for large water transmission systems where energy demand can be shifted slightly without negatively impacting system performance.

Central to the LEEM is the ability to identify the type of marginal generation unit based on the LMP. The marginal unit is the generator capable of supplying that next unit of energy at the cheapest rate. In other words, it is the most expensive generator that is currently dispatched, and therefore, will be the first unit to be incrementally adjusted due to changes in system demands [8]. Since the marginal generator will adjust to changes in demand, each incremental change in electrical use will result in an associated change in pollutant emissions.

Electricity markets in the US encourage utility participants to place generation bid prices based on generation costs. The cost of generation for each power plant can be reasonably approximated using publicly available data [9,10] and calculated as the price of fuel multiplied by the heat rate of that plant. Fuel prices are a function of the type of fuel used. Since the cost of generation is known for many power plants, LMP ranges associated with each fuel type can be determined for similar plants. Additionally, plants with the same primary fuel type are found to have similar air emission profiles. After an LMP is used to estimate the fuel type of the marginal unit, air emissions associated with that type of fuel can be estimated. Various public data sources can be used to estimate emissions from each marginal fuel type [10–13]. This becomes the estimated locational marginal emission and can be used to predict changes in real-time emissions in response to marginal changes in demand.

This paper focuses on improving the LEEM method developed by Carter et al. [2] and evaluating its ability to accurately predict changes in pollutant emissions. Estimations of both generation cost and air emissions are enhanced by incorporating power plant specific data, rather than national average fuel costs and emission rates. The accuracy of the improved model is evaluated against the type of marginal generator and emission estimates predicted by an IEEE model power system. Results from this simulation provide insight into the accuracy the revised method as well as suggestion for future applications.

2. Methodology

For clarity, the earlier version of LEEM created by Carter et al. [2] is identified as LEEM 1.0, while the revised method presented in this paper is described as LEEM 2.0.

2.1. Improvements to LEEM

For LEEM 2.0 *local*, rather than national, fuel prices and emission rates have been employed. As with previous model development, the footprint of the Midwest Independent System Operator (MISO) has been used as the focus region. Despite this development focus, LEEM could be applied to any other LMP-based electricity market.

2.1.1. Classifying generator type

LEEM 1.0 used statewide and nationwide average fuel price reports for coal, natural gas, and fuel oil [14–16] to calculate plant generation costs and develop LMP fuel type price ranges. A refinement implemented in LEEM 2.0 incorporates *unit-specific* reported monthly fuel purchases for each plant, including the quantity of fuel consumed, price paid for fuel, and efficiency (heat rate) of the plant [9,17]. Local regions are defined in LEEM 2.0 by the US EPA's Emissions & Generation Resource Integrated Database (eGRID) subregions [10]. The US EPA identified eGRID subregions using power control areas and North American Electric Reliability Corporation (NERC) regions as a guide [18]. The RFCM (Reliability First Corporation Michigan) area, which covers most of Michigan's lower-peninsula, is used as the subregion for this pilot study.

The plant generation cost (C_i), in dollars per megawatt-hour of electricity produced, was computed as the cost of fuel per heat consumed (F_i) multiplied by the plant's heat rate (H_i), as shown in

$$C_i = F_i \times H_i \tag{1}$$

The EIA-923 form reports the primary fuel type such as natural gas, coal, or petroleum for each plant. These three major fuel types have also been used for LEEM 2.0 (Table 1). In many cases, a more specific fuel type is also reported, such as bituminous or sub-bituminous coal. It was impractical to report each of these specific fuel

Table 1
Fuel types sorted into categories.

Specific fuel types (LEEM 1.0)	Broader category (LEEM 2.0)
Coal-lignite Coal-bituminous Coal-sub-bituminous Petroleum coke	Coal
Natural gas	Natural gas
Distilled fuel oil Residual fuel oil	Oil

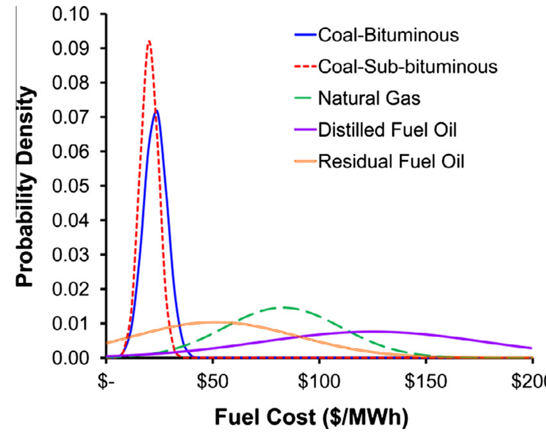

Fig. 1. Normal distribution curves of generation cost for plants in eGRID subregion RFCM, 2009 with specific fuel types.

types separately, as was done for LEEM 1.0. First, certain fuel types often fall into the same range of generation costs, making it very unlikely that the marginal fuel type and prime mover could be determined based on LMP alone. For example, it is nearly impossible to differentiate bituminous or sub-bituminous coal-fired power plants based on generation cost (Fig. 1). Additionally, the ultimate goal of LEEM is to estimate marginal emissions. Though generators at the same power plant may consume different fuel types, the source of emission data utilized for LEEM 2.0 (eGRID) lists power plants by their primary fuel type. As a result, fuel types were categorized as coal, natural gas, or oil.

In LEEM 1.0, LMP price ranges for marginal fuel types were defined crudely by choosing the median of the generation costs for a fuel type, and setting that price as the dividing line between categories. The logic for this approach was that the majority of generators within a specific class would be economically viable beyond this median price point. In LEEM 2.0, an alternative approach was employed, one that utilized probability density curves of plant fuel prices to more accurately identify LMP price ranges. Normal probability density curves were created for each fuel type based on 2009 data for the eGRID subregion RFCM. The price associated with the intersection of the curves for two fuel types reflects the break-point between one marginal fuel type and another (Fig. 2). Using these break-points to define the price ranges, LEEM 2.0 associates each LMP with marginal fuel type as described in

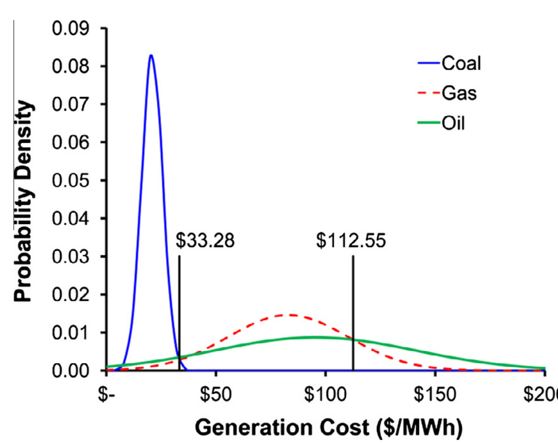

Fig. 2. Normal distribution curves of generation cost for plants in eGRID subregion RFCM, 2009 with consolidated fuel types.

$$primary\ fuel = \begin{cases} Coal & 0 < \text{LMP}_i \leqslant 33.28(\$/\text{MW h}) \\ Gas & 33.28 < \text{LMP}_i \leqslant 112.55(\$/\text{MW h}) \quad i = 1, \ldots, N_{bus} \\ Oil & 112.55 < \text{LMP}_i(\$/\text{MW h}) \end{cases} \tag{2}$$

Generation cost ranges for consolidated fuel types in the RFCM subregion are presented in Fig. 2. The high standard deviation of the generation cost, especially for natural gas and oil, results in a significant amount of overlap in cost associated with each fuel type. This is expected to cause higher error in estimating the marginal generator type, as opposed to a scenario with lower standard deviation of generation costs.

2.1.2. Marginal emissions estimation

Unlike LEEM 1.0, which utilized *national* average emission rates, LEEM 2.0 utilized average *regional* emission rates based on emissions rates of specific power plants reported in the latest version of eGRID [10]. This data was pared down to the local level based on eGRID subregions. Information regarding power plants in each subregion was sorted according to the primary fuel type. Emission rates at each plant for NO_X, SO_2, and CO_2 equivalents are reported in pounds pollutant per megawatt hour of electricity generated. Carbon dioxide equivalents are calculated based on the combined global warming potential of CO_2, CH_4, and N_2O [19]. Average emission rates and standard deviations were calculated for each fuel type and pollutant based on all plants in the region. The average emission rate (μ_{ER}) was weighted based on electricity production at each plant:

$$\mu_{ER} = \frac{\sum(ER_i \cdot NG_i)}{\sum(NG_i)} \tag{3}$$

where ER_i is the emission rate of a specific pollutant from plant i and NG is the net generation at plant i.

A common difficulty in estimating emission rates is that many plants (especially oil-powered plants) have negative net annual generation, meaning that the plant consumed more energy than it produced. In order to deal with impossible negative emission rates, negative net generation was excluded from calculations. It was verified that this practice of excluding negative generation agreed with the EPA's calculations (less than 1% difference for all three pollutants) by comparing the subregion weighted average with eGRID's reported regional rate. The results for the eGRID subregion RFCM, which covers lower Michigan, are presented in Fig. 3.

Calculated local emission rates (Table 2) were compared to those reported by eGRID (Fig. 3). Calculated and reported pollutant emissions for the RFCM subregions were found to be nearly identical but these values were found to vary significantly from eGRID national average [10]. This highlights the importance of using region-specific emissions rates to predict spatially accurate pollutant emissions.

2.1.3. Membership function

As shown in Fig. 2, significant overlap is observed in the prices of fuels used to identify the marginal unit type. Moreover, in reality, it is possible to have multiple marginal units at any given time.

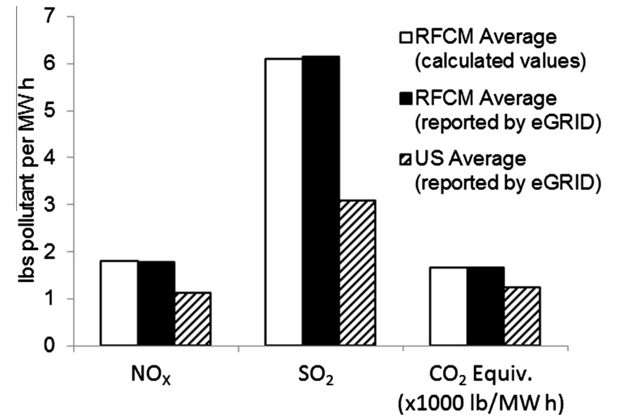

Fig. 3. Local (eGRID subregion RFCM) and national pollutant emissions rates 2009 [10].

These factors decrease the accuracy of emission estimates obtained by the LEEM, which assumes a single marginal unit. Therefore, the use of a membership function (MF) was incorporated into the model to address the possibility of emissions from multiple simultaneous marginal generators. The MF concept is derived from Fuzzy Logic and can increase the likelihood of characterizing the fuel mixture of marginal units. A MF defines how each input data point is mapped to a membership value (degree of membership) between 0 and 1. In our case, the inputs are LMP values and the outputs are the membership values for each fuel type: coal, natural gas and petroleum. Therefore, three membership functions need to be defined, one for each fuel type. To achieve this objective a symmetric Gaussian membership function was employed:

$$f_i(x) = e^{-\frac{(x-\mu_i)^2}{2\sigma_i^2}} \tag{4}$$

where x is the input LMP value; f_i is the degree of membership of ith category (i.e., coal, natural gas or petroleum), μ_i and σ_i^2 are the mean and the variance of the ith category. Details of the MF parameters are listed in Table 5 and the corresponding membership distribution curves are shown in Fig. 4.

The fuel mixture of marginal units was then calculated as

$$percent_i = \frac{f_i}{\sum f_i} \tag{5}$$

where $percent_i$ is the percentage of the ith fuel type generator (coal, natural gas, and oil) at the margin. The overall marginal emission rates can be determined based on the above estimated marginal fuel mixture percentage.

$$ef_j = \sum percent_i \times ef_{ij} \tag{6}$$

where ef_i is the marginal emission factor of emission j and $j = CO_2$, SO_2; NO_X. ef_{ij} is the emission factor of emission j for generator i (coal, natural gas or oil).

Table 2
Local emission rates by plant fuel generation category, RFCM year 2009 data.

Pollutant	Coal		Natural Gas		Fuel Oil	
	μ (lb/MWh)	σ	μ (lb/MWh)	σ	μ (lb/MWh)	σ
NO_X	2.31	0.74	0.49	0.75	24.4	8.1
SO_2	8.27	2.01	0.04	0.35	2.01	0.52
CO_2 equivalents	2159	216	903	413	1911	349

Source: eGRID [10].

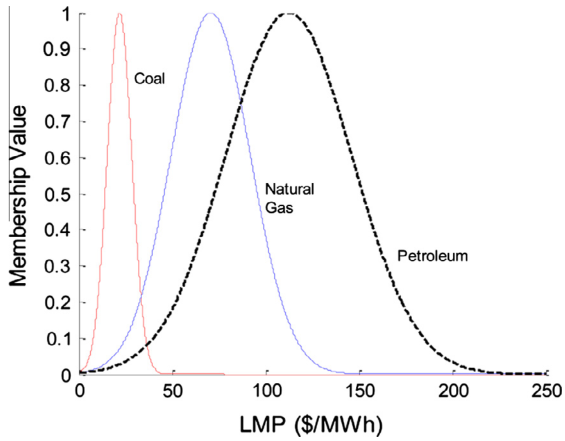

Fig. 4. Membership value distribution of LMP values associated with each generation type.

Table 3
PDF parameters of fuel prices ($/MMBtu) used in simulation studies.

Parameter	Coal	Natural gas	Petroleum
μ	2.05	6.3	9.05
RFCM (% of μ)[a]	0.40 (20%)	1.68 (27%)	4.27 (47%)
σ_1 (% of μ)	0.1025 (5%)	0.315 (5%)	0.4525 (5%)
σ_2 (% of μ)	0.6150 (30%)	1.890 (30%)	2.0715 (30%)

[a] RFCM actual values. Not used in simulation, only presented here as a point of reference.

2.2. Validation of LEEM 2.0 – power system simulation

The LMP-based approach for estimating marginal pollutant emissions lies in the assumption that a change in load on a specific node/bus must be balanced by a change in generation by the marginal generator. Due to the competitive bidding process the LMP at this node directly controls which type of generator will be impacted by this change in demand. Based on this relationship, emissions with respect to the change in load can then be estimated using the average emission rate for the generator class. Verifying the accuracy of LEEM predicted marginal generator types is problematic because the actual marginal generator is not publicly available. The identity of marginal generators is kept confidential to inhibit price gaming in energy markets. As a result, there is no way to *directly* determine whether or not the LMP method is valid.

In the absence of a direct evaluation of real data from an ISO system, a series of simulation studies utilizing a standard IEEE test system were performed to evaluate the accuracy of LEEM 2.0. First, the ability of LEEM to identify the marginal unit using the LMP approach was evaluated. When the marginal unit predicted by LEEM was the same as the dominant marginal unit identified during simulation studies on the IEEE test system this approach was considered to be validated. Second, the ability of LEEM to estimate emission rates was compared against results obtained on the test system using stochastic simulation studies that incorporate variations in fuel prices, system operation conditions and emission factors. Finally, a third set of simulations were conducted to evaluate the incorporation of a MF into LEEM 2.0.

The simulation studies utilized standard stochastic cost and emission models [20]. Three load levels were investigated. For each load level, 200 sampling cases (realizations) were generated. In each case, a 1 MW load increase is applied for every load node and corresponding marginal emissions were calculated. Parameters for the stochastic models were based on fuel pricing and emissions observed in the RFCM subregion (Tables 2 and 3).

2.2.1. Test system

The simulation studies were conducted on a model systems based on the standard 73-bus IEEE Reliability Test System (RTS) [21]. The IEEE RTS system represents a relatively large and complex power system, as it has 73 buses (51 load buses), 99 generators, 120 branches, 16 transformers, and a total of 8550 MW load and 10,215 MW generation capacities. The test system is similar in size to the eGRID subregion RFCM, which the fuel and emission stochastic model parameters were based. The system includes 120 transmission lines at two voltage levels: 138 kV and 230 kV. The generation capacity consists of 900 MW hydro-electric, 2400 MW nuclear, 3822 MW coal, 2853 MW petroleum, and 240 MW petroleum combustion turbine generating units. To mimic the study area for which LEEM was based (MISO), the costs and emissions factors for hydro-electric and nuclear were set to zero. As a result, these generators provided capacity but were always providing base load during the analyses performed. In order to replicate the wide use of natural gas units in the RFCM region, 1080 MW petroleum was replaced with 1080 MW natural gas in the numerical simulation study presented in this paper. The test system was evaluated at 60%, 80%, and 100% of the system load.

2.2.2. Cost model

For a fossil fuel-fired generation unit, the heat rate was modeled as a quadratic function of its active power output [22]. The generation cost of the unit was expressed as

$$C_i(p_i) = F_i(k_{i2}p_i^2 + k_{i1}p_i + k_{i0}) \tag{7}$$

where C_i ($/MW h) denotes the generation cost of generator i; p_i (MW) was the active power output of generator i; F_i ($/MMBtu) denoted the fuel price of generator i; k_{i2}, k_{i1} and k_{i0} were the polynomial coefficients of the heat rate function and were calculated based on the heat rate curve of the generator (see Table 9 in Ref. [21]).

2.2.3. Emissions model

The emission rate of a generator was modeled as proportional to the amount of fuel consumed by the unit per MW h generation [23] as

$$E_{ij}(p_i) = ef_{ij}(k_{i2}p_i^2 + k_{i1}p_i + k_{i0}) \tag{8}$$

Table 4
Emission factors PDF parameters (lbs/MMBtu).

Pollutant	Parameter	Coal	Natural gas	Petroleum
CO_2 equivalents	μ	210	118	162
	σ (5% of μ)	10.5	5.9	8.1
SO_2	μ	0.8	0.005	0.17
	σ (30% of μ)	0.24	0.0015	0.051
NO_X	μ	0.22	0.06	2.1
	σ (30% of μ)	0.066	0.018	0.63

where E_{ij} (lbs/MW h) was emission rate j of generator i; ef_{ij} (lbs/MMBtu) was the corresponding emission factor, which was based on the actual emission rates observed in the eGRID RFCM subregion (Table 4). Typical curves produced from Eq. (8) are presented in the Supplementary data.

2.2.4. Stochastic models

Fuel prices and the emission factors of generators often vary within a characteristic range. In order to simulate reality, stochastic models were used to mimic diverse fuel prices, air emissions and other system conditions. The normal distribution was used to model the stochastic distribution of fuel prices (F_i in Eq. (7)). The probability density function (PDF) of a normal distribution can be described by

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] \quad (x > 0) \tag{9}$$

where μ and σ are the mean and standard deviation of random variable x (fuel prices). Based on the data obtained from the US EIA and EPA regarding power plants located within the eGRID subregion RFCM, the PDF parameters (i.e., μ and σ) of fuel prices for different power plants (i.e., coal, natural gas and petroleum) were obtained and are described in Table 3. Two different standard deviations in fuel prices (σ_1 and σ_2, Table 3) were employed during simulation studies in order to investigate the accuracy of LEEM under scenarios with different variations in fuel prices.

The normal distribution (Eq. (9)) was also used to model the stochastic distribution of emission factors (ef_{ij} in Eq. (8)). The PDF parameters of emission factors listed in Table 4 were used during model simulations. The average emission factors in lbs/MMBtu of fuel consumed were calculated from eGRID data for the RFCM subregion. For the simulation study, standard deviations of 5%, 30%, and 30% of the mean were used for CO_2, SO_2, and NO_X emission rates, respectively (Table 4).

The uniform distribution is used to simulate the on/off state of components in the simulation power system. The PDF of a uniform distribution is

$$f(x) = \begin{cases} \frac{1}{b-a}, & a < x < b \\ 0, & otherwise \end{cases} \tag{10}$$

where $a = 0$ and $b = 1$ for the simulation studies carried out in this paper. To determine the state of transmission line l, for example, a random value is first generated according to the standard uniform distribution on the open interval (0,1). Then, the line state can be determined by comparing the random value with the line availability; if the generated random value is greater than the availability of line l, the line is out of service, otherwise it is in service. Data describing the availability of the transmission lines in the IEEE simulation system can be found elsewhere [22].

A total of three system load levels (60%, 80%, and 100% of the base load) were investigated in the simulation studies. The load at a specific bus was allowed to fluctuate within an appropriate range while maintaining a constant load level for the system. The normal distribution was used to model the load variations at different buses. In other words, the load at a specific node was the product of the base load, a load level coefficient (0.6, 0.8, and 1.0) and a random value generated based on

Table 5
Membership function parameters.

Parameter (\$/MW h)	Coal	Gas	Petroleum
μ	21.86	70.69	112.39
σ (30% of μ)	6.56	21.21	33.72

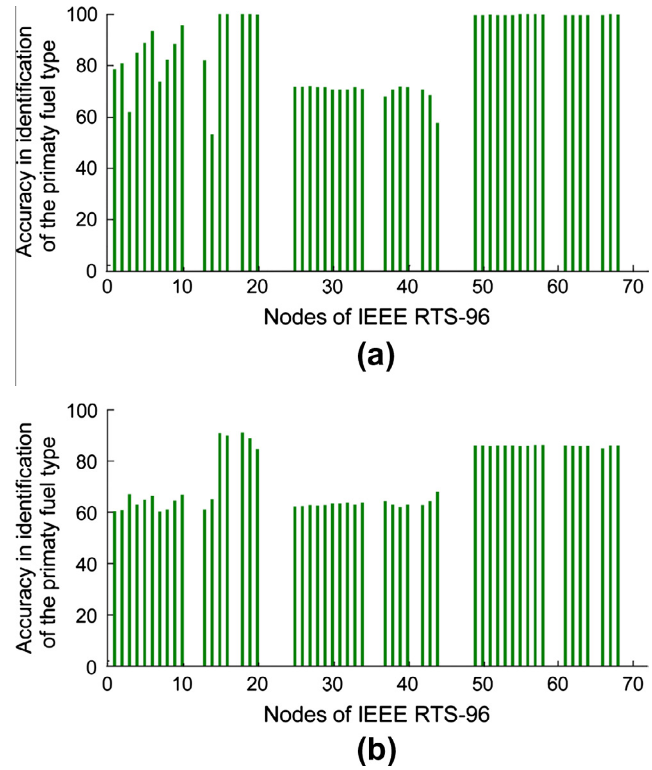

Fig. 5. Accuracy of LEEM in identification of the primary marginal fuel type for the two the fuel price distributions evaluated (a) σ_1 = 5% and (b) σ_2 = 30%.

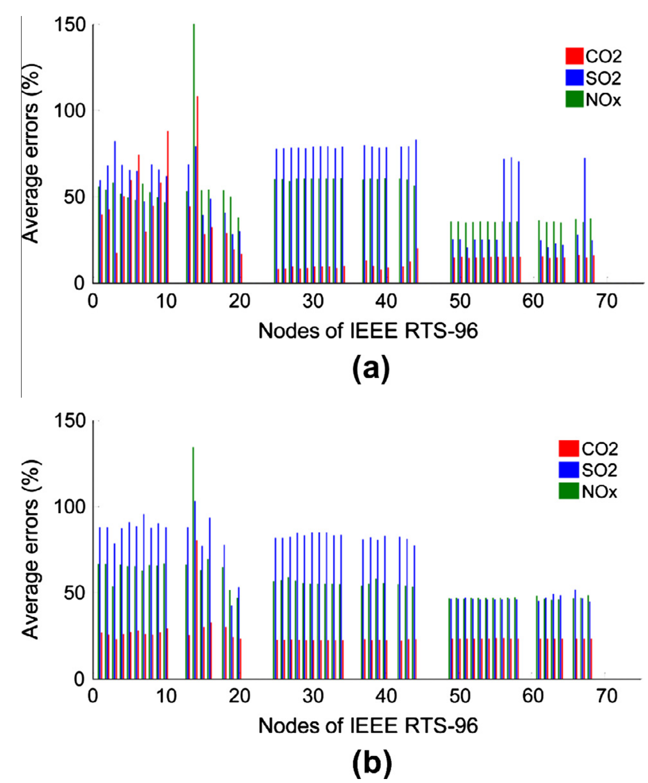

Fig. 6. Percent error in emission estimates from LEEM 2.0 at each node in the IEEE RTS system with (a) 5% deviation and (b) 30% deviation in fuel prices; 5%, 30% and 30% deviations in CO_2, SO_2 and NO_X, respectively.

$$f_i(x) = \frac{1}{\sigma_i\sqrt{2\pi}} \exp\left[-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right] \quad (-\infty < x < +\infty, \quad i = 2, 3, \ldots, N_{bus}) \tag{11}$$

where μ_i and σ_i are the mean and the standard deviation of load at bus *i*. N_{bus} is the total bus number in the system, i.e. N_{bus} = 73. Bus 1 is taken as the reference bus in the simulation system.

3. Simulation results and discussion

3.1. Marginal unit type

Based on the stochastic modeling using fuel prices described in Table 3, the LEEM successfully identified the correct type of marginal unit at the majority of nodes (Fig. 5), even without incorporating a MF. With a 5% standard deviation (σ_1) in fuel prices, LEEM had an accuracy rate of 80% (on average) in identified the primary fuel type of the marginal unit, in response to changes in load (Fig. 5a). When the fuel prices had a 30% standard deviation (σ_2) the model maintained an accuracy of about 70% in identifying the primary fuel type for almost all the load nodes in the system (Fig. 5b). Based on this analysis, it can be concluded that LEEM correctly identifies the primary marginal fuel type a majority of the time for a variety of load conditions and fuel prices.

3.2. Reliability of emission estimates

Based on the stochastic analysis, errors in estimating pollutant emissions using the LEEM ranged from 10% to 150% (Fig. 6). LEEM emission estimates for CO_2 had errors of less than 25% most nodes, regardless of differences in the distribution of fuel prices. The greatest amount of error in estimating pollutant emissions for CO_2, as with all pollutants studied, was observed at node 14. Errors at this node were approximately 100% for CO_2 and SO_2 estimates, and over 150% in NO_X estimates. Estimates of CO_2 emissions related to nodes 1–19 were generally found to be greater when fuel prices had a smaller deviation in price (Fig. 6a) than when they had a larger deviation in price (Fig. 6a). This was generally opposite the

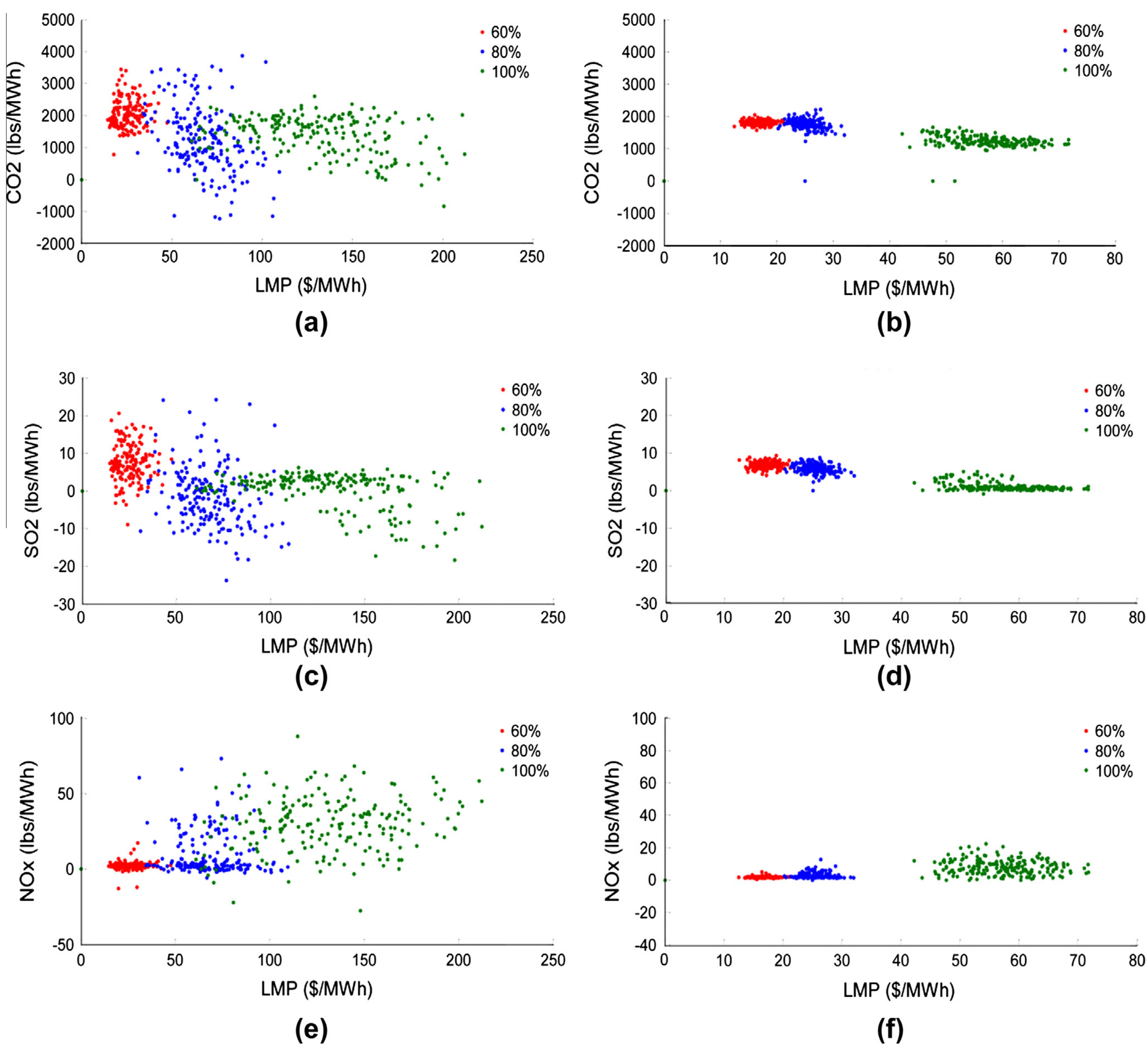

Fig. 7. Marginal CO_2 , SO_2, and NO_X emissions under different load conditions at bus 14 (left panel; a, c, and e) and bus 20 (right panel; b, d, and f).

trend that was observed for other pollutants. For a majority of load buses, NO_X emission estimates were generally less than 60%, regardless of deviations in fuel prices. Again, node 14 was found to have the greatest amount of error in estimating NO_X emissions. Sulfur dioxide was generally was found to have the greatest amount of error associated with pollutant emission estimates. For SO_2 over 65% of load buses had errors greater than 50%. When fuel prices varied by 30% (Fig. 5b), most of the buses were found to have emission estimate errors around 80%.

The accuracy of pollutant emission estimates was found to vary by pollutant, node and the variability of fuel prices. Greater deviations in fuel prices (i.e. standard deviation 30%, rather than 5%) did not have an equal impact on all pollutants. This may be partially attributed to the variability of CO_2, SO_2 and NO_X emission rates (5%, 30% and 30%) used during the simulation studies. These deviations were present even when there was little variability in fuel prices and fuel price ranges did not overlap, which would result in a 100% correct identification of generation types.

Fig. 7a, c, and e shows the detailed marginal emission data for all the 600 simulation studies (200 points for load levels of 60%, 80% and 100%) at bus 14. Fig. 7 was developed assuming a fixed 30% deviation in fuel prices and 5%, 30% and 30% deviations in CO_2, SO_2 and NO_X emission rates, respectively. The LMP reported for bus 14 by the IEEE model system had a large range of LMP values, 20–200 \$/MW h. These results suggest node 14 may be located in a constrained area when the system load level increases. A constrained condition can cause large variations in LMP prices, which may lead to large errors in emission estimation. For the purpose of comparison, the emission data for bus 20, which is a typical bus with a smaller emission rate estimation error, are given in Fig. 7b, d, and f. Note a narrower range of LMP prices were observed at bus 20 relative bus 14 and, as a result, more accurate pollutant estimates were observed at this bus (Fig. 6). Additionally,

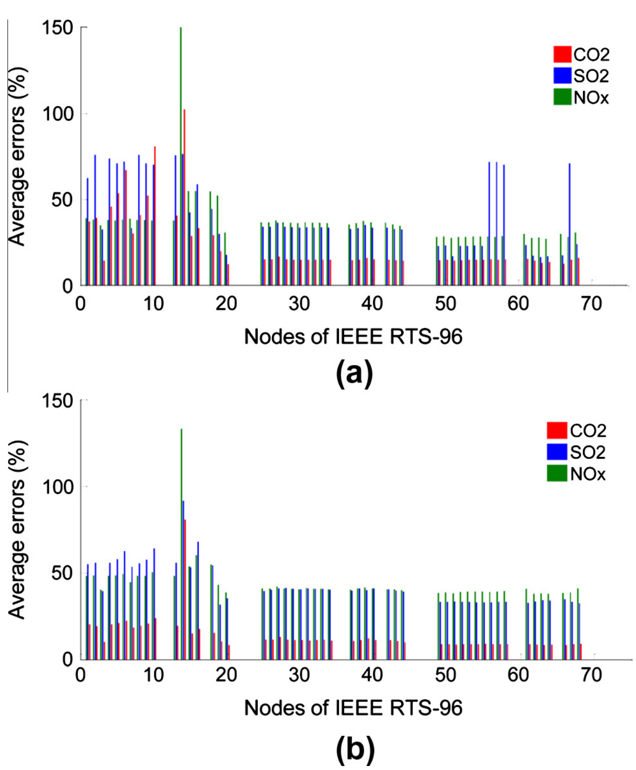

Fig. 8. Percentage errors in estimating emissions at different nodes using the LEEM with MF method with (a) 5% deviation and (b) 30% deviation in fuel prices; 5%, 30% and 30% deviations in CO_2, SO_2 and NO_X, respectively.

these estimates were found to be generally less susceptible to variations fuel prices.

Another reason for large emission estimation errors associated with LEEM is that there can be multiple marginal generators that respond to a 1 MW increase in load. For example, to accommodate a 1 MW load change, there can be 0.5 MW supplied by a coal-fired generator(s) and the remaining 0.5 MW from natural gas fired unit(s) if power loss is neglected. Moreover, there can be a reduction in the output of some generator(s) while the other marginal units will supply even more. For instance, for a 1 MW load increase under different conditions, there may be a 2 MW reduction in coal-fired marginal units while a 3 MW increase in natural gas fired generator(s). The reduction (or negative increase) in certain units can cause negative values of marginal emissions, as observed in Fig. 7, particularly for bus 14.

3.3. Membership function method

Incorporating a membership function into the LEEM significantly reduced the emission estimation errors for CO_2 and SO_2 (Fig. 8). For most of the load buses, the errors in estimating CO_2 emissions have been reduced to around 20% while the errors in estimating SO_2 and NO_X have been reduced to less than 40% for a majority of nodes. However, as shown in Fig. 8, significant errors continue to be observed at bus 14. The use of a MF becomes less effective at 5% deviations in fuel prices. This is consistent with the results observed without a MF where the ability of the LEEM to correctly identifying the fuel type improves with smaller variations in fuel prices (Fig. 5a). Nevertheless, the LEEM with a MF provides emission estimates with errors less than 50% for the majority of nodes, even with the high variations in fuel prices that can be observed in the RFCM (Table 3).

4. Conclusions

The LMP Emissions Estimation Method, LEEM, was improved to include local emission rates and fuel prices based on historic electric power plant data. The power system simulation study indicates that LEEM can successfully determine the marginal generator unit type 70% of the time with 30% deviation in fuel prices and 80% of the time with 5% deviation in fuel prices. Without including a MF in LEEM, marginal emission estimates have errors less than 25% for CO_2, and higher errors for NO_X and SO_2. The inclusion of a MF into LEEM improves the models ability to predict pollutant emissions. This results in less than about 20% error for CO_2 estimates and generally less than 50% error for NO_X and SO_2 estimates. This improvement in predictive ability virtually eliminates problems associated with deviations in fuel prices.

It should be noted that LEEM utilizes differences in fuel prices that dictate the type of generation unit. If the current price structure changes significantly and the costs ranges for different generation/fuel types overlap then it is unlikely the method could provide accurate estimates based on LMPs. In the future, an alternative method for identifying locational marginal emissions (LMEs) may be necessary due to the lack of a clear difference in generation costs between units with distinct emission factors. In addition to changes in fuel prices, advances in emission control equipment may also magnify errors associated with grouping generators based on fuel type alone.

LEEM appears to be effective at providing general estimates that could be used to rapidly evaluate demand side energy decisions based on pollutant emissions. If these estimates could be used to shift loads over sustained periods of time, pollutant emissions are likely to be reduced. Additionally, LEEM could be used to effectively evaluating energy policies. For example, the US EPA released

Mercury and Air Toxics Standards (MATS) in 2011. These regulations define new limits for mercury, acid gases, and non-mercury metallic toxic pollutants for coal and oil-fired power plants [24]. Though these rules are still undergoing public comment and revision, power generators must be ready to comply when they are implemented. A potential approach to reducing MATS is to influence demand-side decisions. Previously this approach was considered infeasible because no method for rapidly estimating pollutant emissions was available. It may be possible to achieve these reductions without reducing power demand by shifting loads to times when the pollutant emission profile is different. The LEEM provides the rapid assessment of pollutant emissions that will enable demand-side decisions and optimizations to be made to reduce pollutant emissions.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2013.05.057.

References

[1] Van Atten C, Saha A, Reynolds L. Benchmarking air emissions of the 100 largest electric power producers in the United States; 2012.
[2] Carter TH, Wang C, Miller SS, McElmurry SP, Miller CJ, Hutt IA. Modeling of power generation pollutant emissions based on locational marginal prices for sustainable water delivery. In: Energytech, 2011 IEEE. Cleveland (OH): IEEE; 2011. p. 1–6, http://dx.doi.org/10.1109/EnergyTech.2011.5948499.
[3] Hamoud G, Bradley I. Assessment of transmission congestion cost and locational marginal pricing in a competitive electricity market. IEEE Trans Power Syst 2004;19(2):769–75.
[4] Hausman E, Fagan R, White D, Takahashi K, Napoleon A. LMP electricity markets: market operations, market power, and value for consumers. Cambridge (MA): Synapse Energy Economics, Inc., American Public Power Association; 2006.
[5] Stoft S. Power system economics: designing markets for electricity. IEEE Press, Wiley-Interscience; 2002.
[6] Cheung KW. Standard market design for ISO New England wholesale electricity market: an overview. Electric utility deregulation, restructuring and power technologies, 2004 (DRPT 2004). In: Proceedings of the 2004 IEEE international conference, vol. 1; 2004. p. 38–43.
[7] Midwest Independent System Operator (MISO). Historical LMP market report; 2008. <https://www.midwestiso.org/Library/MarketReports> [accessed 12.12.12].
[8] Pfeifenberger J, Spees Kathleen, Schumacher Adam. A comparison of PJM's RPM with alternative energy and capacity market designs. PJM Interconnection, The Battle Group. 2009:1–90.
[9] U.S. Energy Information Administration. Form EIA-923 annual electric utility data; 2012.
[10] U.S. Environmental Protection Agency. Emissions & generation resource integrated database (eGRID), Version 1.0; 2012.
[11] U.S. Environmental Protection Agency. Toxics release inventory (TRI); 2012.
[12] U.S. Environmental Protection Agency. Web factor information retrieval data system (WebFIRE), Version 6.25; 2010.
[13] U.S. Environmental Protection Agency. Air markets program data (AMPD); 2012.
[14] U.S. Energy Information Administration. Annual coal report: independent statistics and analysis; 2011.
[15] U.S. Energy Information Administration. Natural gas navigato: independent statistics and analysis; 2011.
[16] U.S. Energy Information Administration. Petroleum navigator: independent statistics and analysis; 2011.
[17] Federal Energy Regulatory Commission. Form FERC-423 data. Commission FER; 2007.
[18] Rothschild SS. Total, non-baseload, eGRID subregion, state, guidance on the use of eGRID output emission rates. Springfield (VA): E.H. Pechan & Associates, Inc. for the U.S. Environmental Protection Agency; 2009. p. 4.
[19] Forster P, Ramaswamy V, Artaxo P, Berntsen T, Betts R, Fahey DW, et al. Changes in atmospheric constituents and in radiative forcing. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller ML, editors. Climate change 2007: the physical basis. Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change. New York (NY, USA): Cambridge University Press; 2007.
[20] Shao M, Jewell WT. CO_2 emission-incorporated ac optimal power flow and its primary impacts on power system dispatch and operations. In: Power and energy society general meeting, 2010 IEEE; 2010. p. 1–8.
[21] Grigg C, Wong P, Albrecht P, Allan R, Bhavaraju M, Billinton R, et al. The IEEE reliability test system-1996. A report prepared by the reliability test system task force of the application of probability methods subcommittee. IEEE Trans Power Syst 1999;14(3):1010–20.
[22] Wang C, McElmurry SP, Miller CJ, Zhao J. An integrated economic/emission/load profile management dispatch algorithm. In: IEEE PES general meeting 2012. San Diego (CA): IEEE; 2012, http://dx.doi.org/10.1109/PESGM.2012.6345405.
[23] Talaq JH, El-Hawary F, El-Hawary ME. A summary of environmental/economic dispatch algorithms. IEEE Trans Power Syst 1994;9(3):1508–16.
[24] U.S. Environmental Protection Agency. Mercury and air toxics standards (MATS); 2013.