Developing Real-Time Emissions Estimates for Enhanced Air Quality Forecasting

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Exploring the relationship between ambient temperature, energy demand, and electric generating unit point source emissions and potential techniques for incorporating real-time information on the modulating effects of these variables using the Mid-Atlantic/Northeast Visibility Union region as an example.

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The operation of air quality forecast models (AQFMs) based on coupling a numerical weather prediction (NWP) model to an emissions processor and a chemical transport model (CTM) are now common within the United States.[1-8] Health professionals and air quality managers utilize these forecasts to alert susceptible populations and the public at large of poor air quality conditions and recommended actions to minimize exposures. In addition, air quality forecasts have the potential of guiding emission interventions designed to mitigate episodic events and exceedances of National Ambient Air Quality Standards (NAAQS).

While the NWP component incorporates a large amount of real-time information in the form of initial conditions and analysis fields, the emissions processor often relies on simplifying assumptions about the magnitude and temporal-spatial variation of emissions. Emissions of nitrogen oxides (NO_x) and sulfur dioxide (SO_2) from major point sources are directly measured, tracked, and archived via the U.S. Environmental Protection Agency's (EPA) continuous emissions monitoring (CEM) network in support of the Clean Air Markets Division for emissions cap-and-trade programs (see www. epa.gov/captrade). Unfortunately, it is not feasible to incorporate these emission measurements in real-time into AQFMs.

The development of an approach to enhance short-term emissions estimates is expected to improve the overall performance of AQFMs and, specifically, the performance associated with episodic events. The inherent relationships between weather fluctuations, electricity demand, emissions, and air quality are not currently represented in the emissions processing module of AQFMs.

Enhanced Emissions Estimates

The emissions model applied in AQFMs typically derives emissions from annual totals of emitted species by source category that are allocated monthly and then hourly based on averaged temporal profiles. Some source categories, such as

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electric generating units (EGUs) exhibit significant daily variations in emissions as compared to their means, especially during periods of peak electrical power demand. Point source emissions are measured and archived as part of EPA's network of CEMs. The archived hourly averaged data are typically available within a year of collection and are also used to refine emissions inventories for modeling in State Implementation Plans.

The variation in EGU emissions can be observed by comparing their actual and average hourly emissions, where "actual" refers to measured hourly emissions from CEMs for EGUs on a unit-by-unit basis and "average" refers to the hourly emissions derived from annual emission totals using averaged temporal profiles (i.e., monthly, daily, and hourly profile) based on the actual 2007 CEM data on a state-by-state basis.[9]

Figure 1 shows the time series of daily emissions for the actual and average NO_X emissions in tons/day during summer of 2007 in the Mid-Atlantic/Northeast Visibility Union (MANE-VU) region. The average emissions show the monthly and weekday–weekend patterns used in their allocation of the annual emissions; Figure 2 shows the extent to which the actual and average NO_X emissions differ on a daily basis. Differences in EGU emissions typically occur on days of high energy demand which is associated with high ambient temperatures.

On days of high energy demand, additional generators are brought online for power generation. These units are referred to as "peaking units" and typically operate less than 15% of the time during the year.[10] Figure 3 shows the NO_X emissions from peaking units in the MANE-VU region from May to September 2007. It illustrates the significant contribution peaking unit emissions can have on some days. It should be noted that, depending on federal and state reporting requirements, not all peaking units may be equipped with CEM and, therefore, cannot be considered in this analysis.

Preliminary air quality modeling studies indicate that time periods when the actual emissions were larger than the average emissions (i.e., positive difference) usually coincided with days leading to high ozone (O_3) concentrations.[11] The impact of differences in point source NO_X emissions between the two scenarios on O_3 predictions varied by location, with the largest changes at the grid cells adjacent to the affected point sources. The maximum difference in 1-hr or 8-hr daily maximum O_3 was typically greater than 4 parts per billion (ppb) around the Ohio River valley, and less than 2.5 ppb in general. Differences as large as 8–10 ppb were noted at selected monitor locations in the MANE-VU region, illustrating the need for refined emissions in air quality modeling. In the following section, we present an example approach of incorporating the relationships between energy demand and emissions into AQFMs.

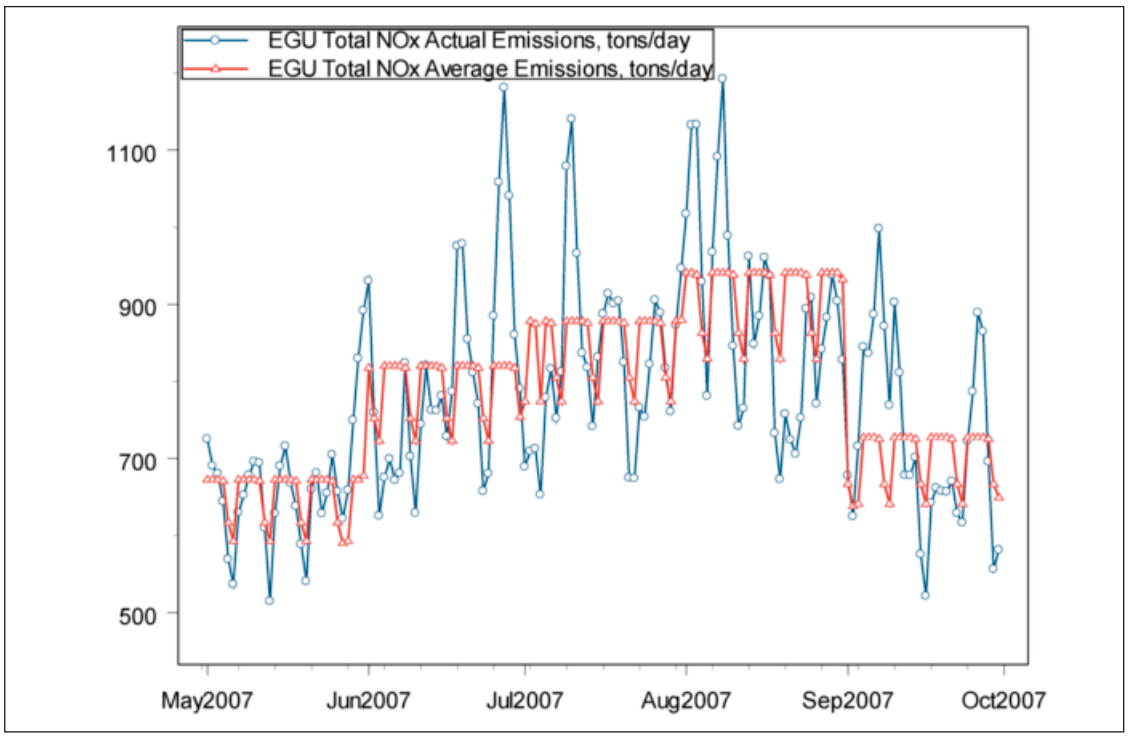

Figure 1. Actual daily and average EGU NO_X emissions in the MANE-VU region.

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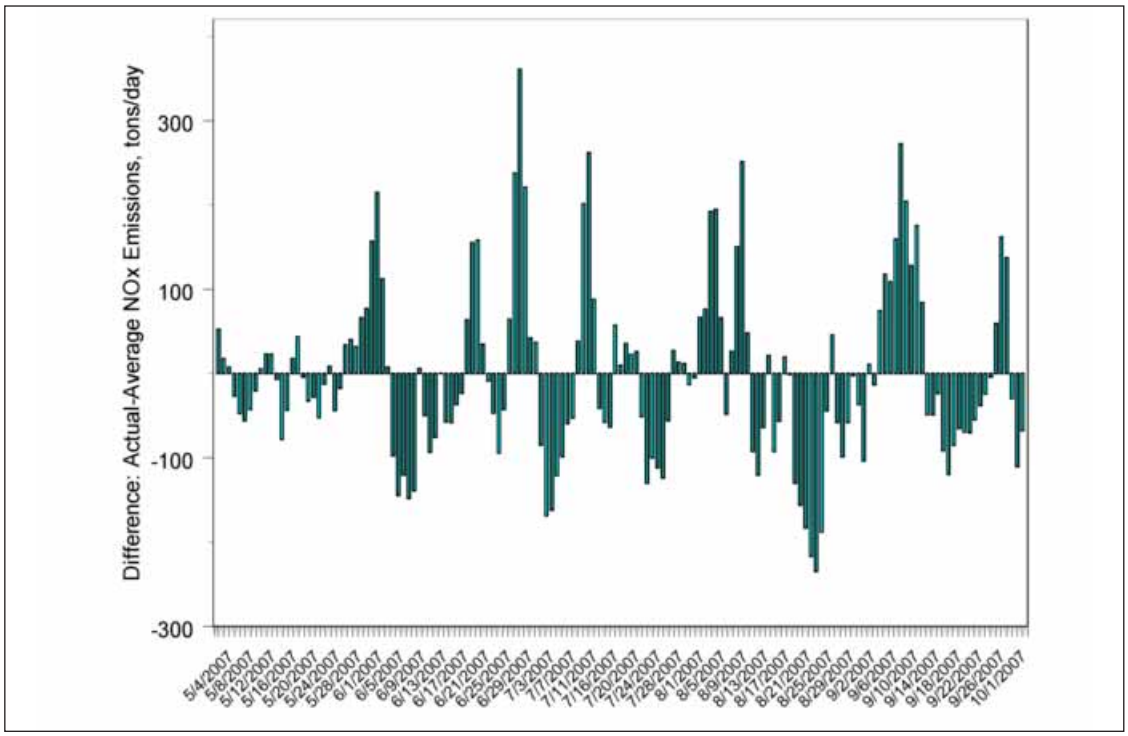
Figure 2. Difference in actual daily and average EGU NO_X emissions in the MANE-VU region.

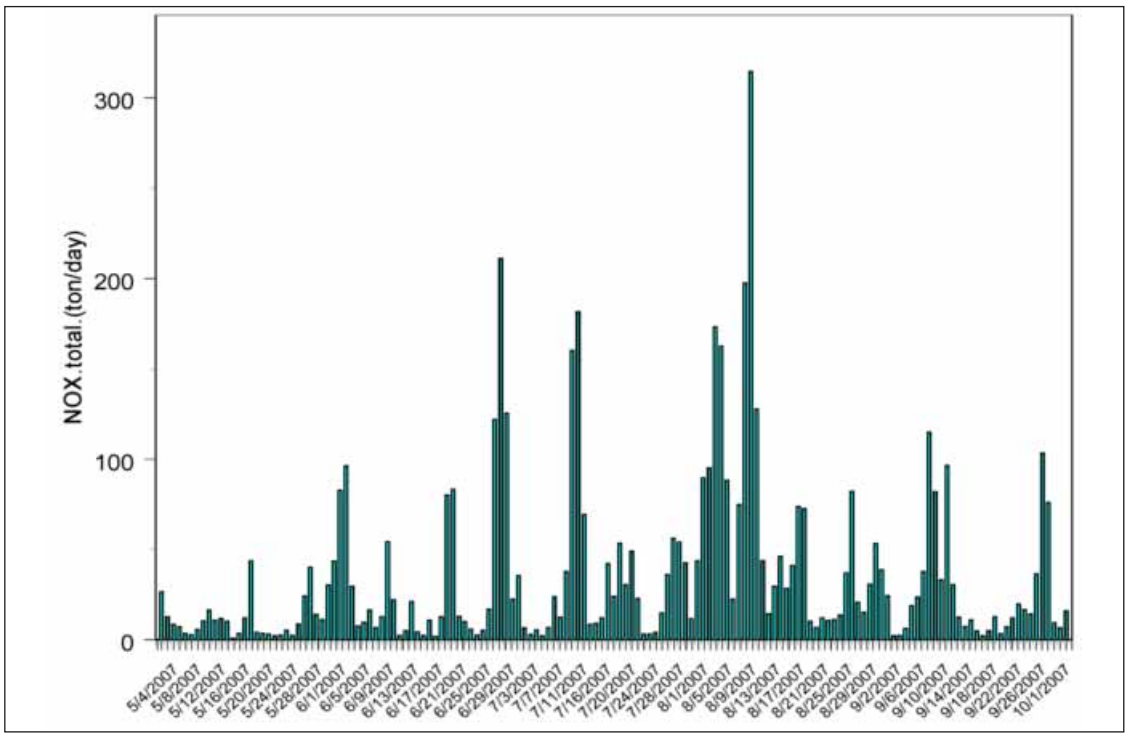


Energy Demand Forecasts

Regional independent system operators (ISOs) perform daily energy forecasts as part of their mission to ensure efficient generation and flow of power to satisfy energy demand and administer electricity markets. These forecasts are typically available online. ISOs in operation within the eastern United States include the New York ISO (NYISO),[12] the New England ISO,[13] the Midwest ISO,[14] the PJM Interconnection,[15] and the Southeastern Electric Reliability Council.[16] The availability of real-time energy load forecasts in principle provides an opportunity to enhance real-time EGU emissions estimates for AQFMs.

For example, a comparison of 2007 CEM NO_X emissions and NYISO forecast energy load data shown in Figure 4 indicates a robust correlation between these variables. In addition, a comparison of actual and forecast energy load data from this

Figure 3. NO_X emissions from "peaking units" in the MANE-VU region from May to September 2007.



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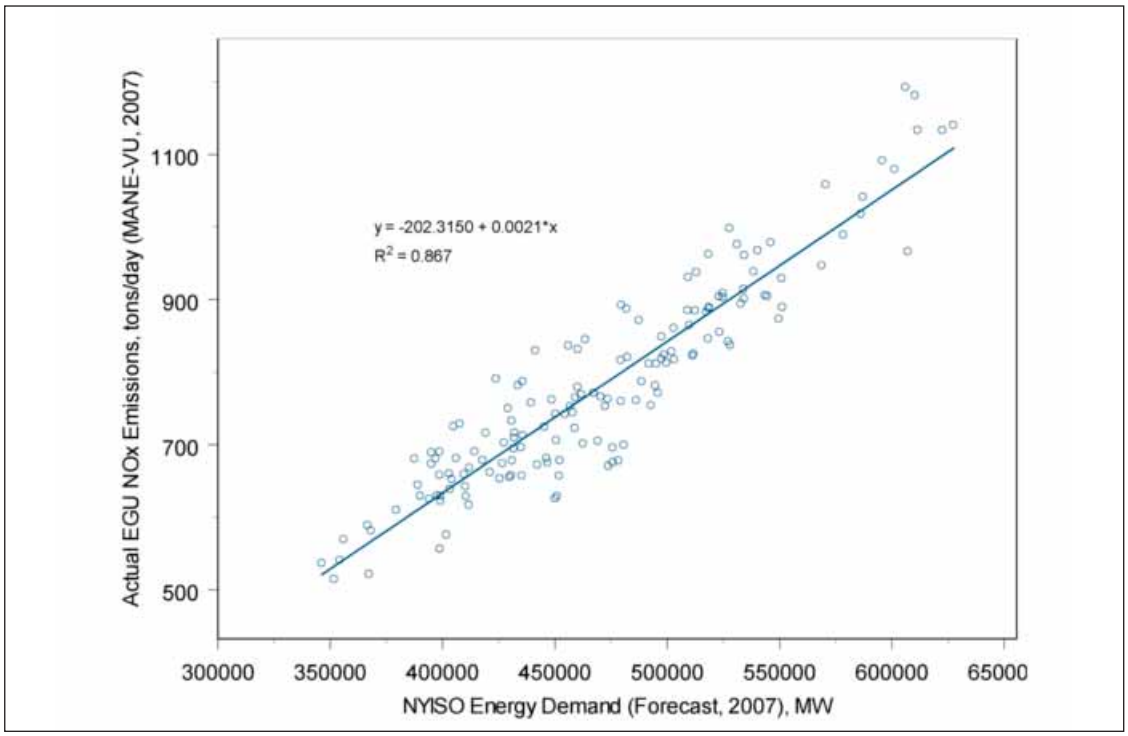

Figure 4. NYISO forecasted energy demand and actual daily CEM EGU NO_X emissions in the MANE-VU region.

same period (not shown) reports a correlation coefficient of $R^2 = 0.954$, indicating that load forecasts provide an opportunity to improve daily EGU emission estimates.

Incorporating emissions from peaking units on a real-time basis requires taking into account the relationship of between meteorology, energy demand, and EGU unit operation. The dominant meteorological parameter affecting the energy demand forecast is temperature.

Energy Load-Adjusted EGU Emissions Estimates

Historical power load data from the NYISO archive[12] and temperature observations data from the research data archive[17] at the National Center for Atmospheric Research have been analyzed for statistical relationships between daily power load and average temperature in NY State.

Figure 5 shows a quadratic relationship between ozone season temperature data (May–September) from 2007 to 2009 and the actual power load for the NYISO region aggregated over NY State. The regression model is: power load (MW) = $288.6112x^2 - 2.9463E+4x + 1.1487E+6$ Where, x = average daily temperature (which ranged from 45 to 81°F) and $R^2 = 0.7554$.

A comparison between the model-predicted power load using the above relationship and the actual power load for 2010 is shown in Figure 6 with an R^2 of 0.8039. A similar comparison for 2011 (not shown) had an R^2 of 0.8113. Since the results indicate reasonable performance of the regression model, the correlations can be employed to support a better forecast. As the range of daily average temperatures during 2007 to 2009 for the model development was up to 81 °F, predictions of power load at temperatures above 81 °F suggest possible over prediction and the potentially greater influence of EGU peaking units.

Although energy load is distributed across ISO regions and across states, energy use within a region does not necessary reflect where the power is generated and thus where emissions occur. If a significant portion of the electric generation to meet load demand occurs outside of the aggregated ISO domains, the relationship between forecasted load and EGU emissions will be more uncertain. In addition, EGU emissions will vary over the years due to emission controls and changes in electric generation capacity and load demand; the latter very likely affecting the operating frequency of peaking units.

Methodologies for Incorporating Real-Rime EGU Emissions Estimates in AQFMs

Current analyses indicate that two methodologies look feasible for incorporating real-time EGU emissions estimates in AQFMs. The first approach

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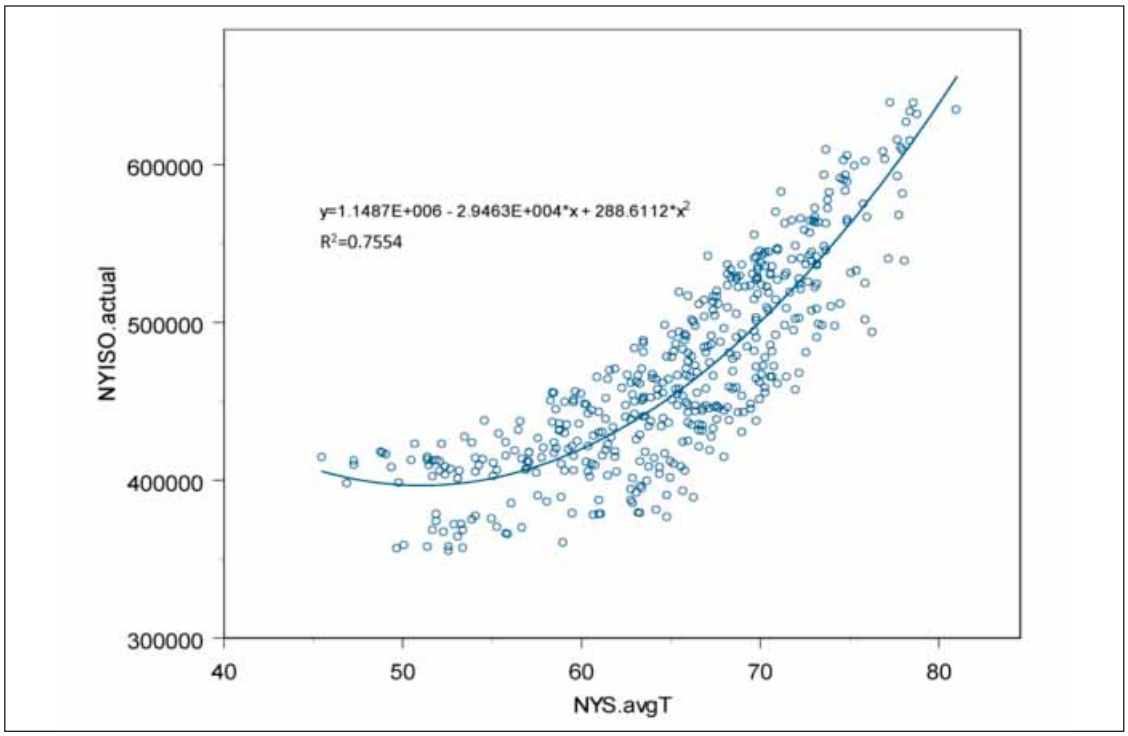

Figure 5. Regression model between NYISO actual power load (MW) and NY state wide daily average temperature (°F) developed using ozone season data (May–September) from 2007 to 2009.

considers aggregating (by state) the hourly energy load forecast data (day 2) from the ISOs for preprocessing by the Sparse Matrix Operator Kernel Emissions (SMOKE) processor.[18] The SMOKE preprocessing will involve incremental adjustments of EGU unit emissions at the state level and on daily average basis, reflecting the statistical relationship between previous years' energy load and emissions data.

The second approach draws from the relationship between temperature–energy load and EGU emissions and is more indirect, but also does not rely on the ISOs real-time energy load forecasts. In this case, forecasted temperatures used to process other emission components in the SMOKE emissions model will be applied to the statistical relationship between previous years' daily average temperatures and actual energy load data by state. As tem-

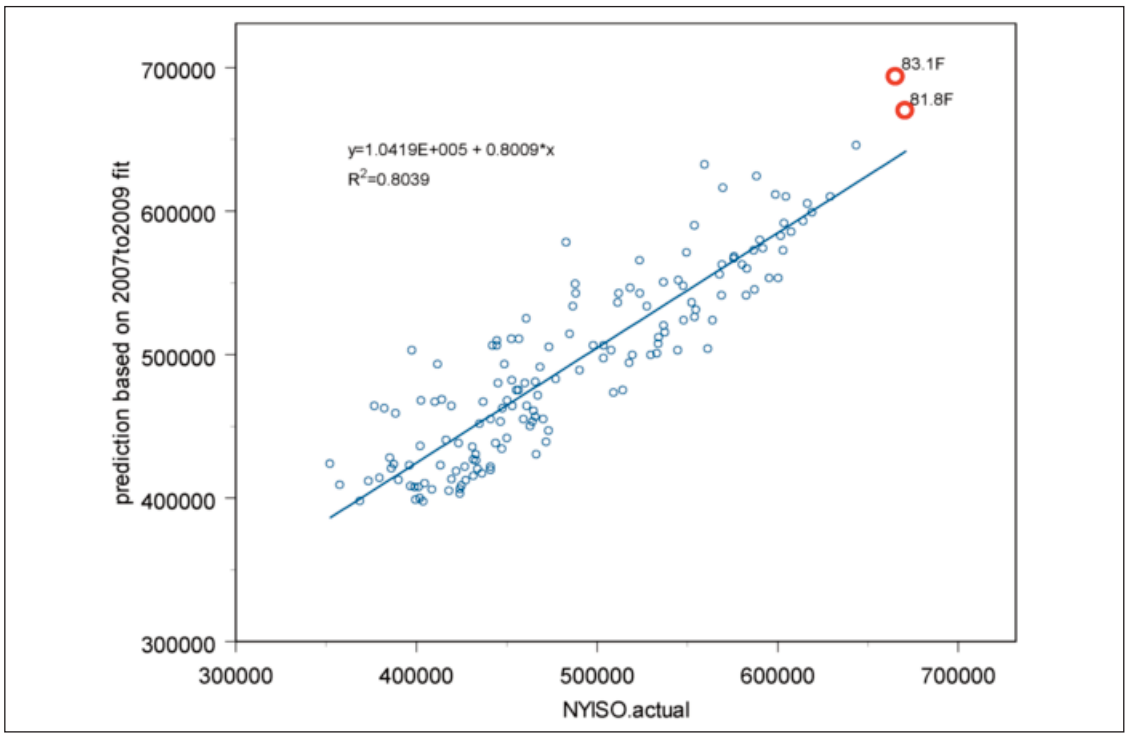

Figure 6. Prediction of 2010 power load with the regression model vs. 2010 NYISO actual power load (MW).

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perature has been shown to be a reasonable surrogate for energy load, using a direct relationship between temperature and EGU emissions is also feasible. In either case, similar procedures for the SMOKE preprocessing of the ISO energy load in relation to emissions would be followed.

Future Challenges and Outlook

AQFMs are being used by air quality managers and health officials to issue air quality advisories. Improving the accuracy of air quality forecasts will translate into providing more precise warnings to the public. In this article, we presented an example of possible approaches to refine the characterization of emissions from power plants in AQFMs. We explored relationships between ambient temperature, energy demand and EGU point source emissions and suggested methodologies for applying these relationships to enhance real-time EGU emissions estimates for use in AQFMs. However, there are some limitations.

While the relationships presented here are robust, they were developed based on aggregated emissions sources in NY State, and as such, may be best suited to improve regional-scale predictions.

Developing unit-specific relationships will be much more challenging because load forecasts are not available at that level, and economic and operational constraints likely are at least as important as meteorology in determining which unit runs on which day at which level.

Finally, depending on federal and state reporting rules, some of the peaking units with relatively small annual emissions may not be required to have CEM. Therefore, their annual total emissions are currently included in the miscellaneous point source category inventory and no further information on their temporal variation is readily available. Getting a better representation of their temporal variability may be important for finer scale applications, but is a challenge that may need to be addressed in the future.

The potential of an air quality forecast system is its possible utility as a dynamic air quality management tool that can provide information on likely emission intervention strategies that can avoid air quality exceedances. Improving the accuracy of the model predictions through refinements such as that discussed in this article is an important step toward achieving that goal. **em**

Improving the accuracy of air quality forecasts will translate into providing more precise warnings to the public.

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