Sustainable Energy Technologies and Assessments 30 (2018) 150–163

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

journal homepage: www.elsevier.com/locate/seta

Energy-related emissions from commercial buildings: Comparing methods for quantifying temporal indirect emissions associated with electricity purchases

Zahra Fallahi, Kaden Plewe, Amanda D. Smith*

Site-Specific Energy Systems Laboratory, Department of Mechanical Engineering, 1495 East 100 South, MEK 1550 University of Utah, Salt Lake City, UT 84112, United States

ARTICLE INFO

Keywords:
CO_2 emissions
NO_x emissions
SO_x emissions
Commercial buildings
Building energy modeling

ABSTRACT

The emissions associated with purchased electricity in a specific location are determined by the emission factors attributed to power generators on the electrical grid serving a facility. Averaged, flat rate emission factors consider a representative fuel mix in a region, usually averaged over many years, and are often used in conjunction with building energy analysis. Time-varying power generation data is needed to determine the effect of power generation dispatch on marginal emission factors, but such data is rarely publicly available. This work provides a critical comparative analysis of two types of temporal emission factors with the goal of understanding how indirect emissions relate to the energy usage of commercial buildings in the U.S. Every building's consumption of electricity also varies temporally, so we use representative electric loads on an hourly basis using stock building model simulations. The methods compared are: (1) regional factors provided by U.S. Environmental Protection Agency (EPA) power generation data and (2) city-specific factors derived from the Locational Emissions Estimation Methodology (LEEM). The emissions resulting from alternate calculation methods are presented for , NO_x, and SO_x. These locally specified, hourly resolved methods of indirect emissions calculation were found to differ from the simple flat rate emissions calculation method (4%–20%). On an annual basis, the difference in calculated emissions using hourly emission factors versus annually averaged LEEM and EPA factors differed by less than 2%, indicating that they provide similar information on an annual basis.

Introduction

Atmospheric CO_2 concentrations passed the 400 ppm level in 2016 [1], and anthropogenic emissions from the total built environment continue to rise. Decreasing the rate of emissions production from anthropogenic systems is necessary to slow or halt the trend of increasing concentrations of atmospheric CO_2 and other greenhouse gases (GHGs). The main GHGs contributing sectors in the United States are transportation, industrial, residential, and commercial buildings, with the buildings sector contributing to more than 40% of total CO_2 emissions [2]. Worldwide, commercial buildings present many opportunities to reduce CO_2 emissions [3]. Gutierrez-Aliaga and Williams have calculated that changes to thermostat settings in offices and restaurants in the U.S. alone could reduce their CO_2-equivalent annual emissions by 1% [4].

Building emissions are categorized as direct or indirect based on their discharge location. Direct emissions from on-site combustion can be mitigated using energy efficiency retrofits, [5], or by implementing energy management strategies and sophisticated control systems to optimize operating schedules [6]. The majority of indirect emissions from the buildings sector are associated with regional power generation and are discharged at power plants that supply electricity to the electrical grid. Various methods are used to consider the amount of indirect emissions associated with the electricity purchases of buildings [7].

Averaged emission factors are calculated based on the share of different resources in electricity production [8]. In the United States, state-based data is available for calculating emission factors. For example, in the state of Michigan, monthly electricity production in August 2017 came primarily from coal (37%), nuclear (31%), natural gas (25%), and renewables (less than 6%); in Indiana, monthly electricity production in August 2017 came from coal (78%), natural gas (18%), and renewables (less than 4%). Although averaged emissions factors are based on the types of power plants generating the electricity in each region, they do not consider the effects of the climate, load patterns, and grid communications and operations. This could reduce the

* Corresponding author.
E-mail address: amanda.d.smith@utah.edu (A.D. Smith).

https://doi.org/10.1016/j.seta.2018.09.004
Received 16 December 2017; Received in revised form 25 August 2018; Accepted 5 September 2018

Nomenclature

Nomenclature

GHG	Greenhouse Gas
EIA	Energy Information Administration
LMP	Locational Marginal Price
EPA	Environmental Protection Agency
eGRID	Emissions & Generation Resource Integrated Database
LEEM	Locational Emission Estimation Methodology
RT	Real Time
DA	Day Ahead
MISO	Midcontinent Independent System Operator
CPN	Commercial Pricing Node
DOE	Department of Energy
TMY	Typical Meteorological Year
BEM	Building Energy Modeling
HVAC	Heating, ventilation, and air conditioning
E_i	Hourly energy consumption (at hour i)
EF_i	Hourly Emission Factor (at hour i)
D_i	Difference between Emission Factors at time step i
σ	Standard deviation
μ	Average difference between emission factors (mean D_i)
SD	Standard Deviation

effectiveness of emission-based policies if the reductions in load happen at unfavorable times or create load ramping requirements that result in a more emissions-heavy generation profile overall. Therefore, for a more precise estimation of indirect emissions production from building operations, temporal electricity production and temporal emission factors should be used rather than time-averaged values.

Temporal electricity production

Detailed emission calculations can be procured if time variable emission factors are available. Time variable emission factors may account for:

- **diurnal** variations in electricity demand, which introduce a dependency between the electricity market and demand forecast.
- **seasonal** variations in electricity demand, which account for load differences based on the prevalence of heating or cooling loads, as an example.
- **interannual** variations in electricity demand, which account for load differences based on the unique characteristics of the given calendar year, such as extreme temperatures.

In this work, the effects of diurnal and seasonal variations are accounted for in varying levels of detail. Capturing the effects of interannual variations requires much more year-specific data than is currently publicly available.

Weather conditions are one critical factor in demand. Weather elements that vary seasonally or extreme and unexpected weather episodes can change both the demand and the peak load production. Lin [9] attempted to capture this transient effect in the calculation of indirect electricity by electricity purchases of commercial buildings in China; however, only coal power plants were considered. A simple model considering only one type of power plant cannot represent the complexity of a geographically diverse electricity market and the effects of marginal generators. In electrical grids, the amount of the marginal electricity demand and the dynamics of grid dispatching and balancing at any time will determine the locational marginal pricing (LMP) [10]. LMP data is publicly available across different Independent System Operators in the United States [11,12]. Algorithms can predict the unit providing the marginal electricity demand given data about the LMP and the availability of power production units in the regional grid. This enables researchers to calculate and predict the temporal behaviour of emissions associated with power production [13].

EPA emission factors

The National Renewable Energy Laboratory [14] has published a database of temporal emissions factors for U.S. regions using EPA data [15]. The LMP-based method utilizes the GridView™ software to calculate the hourly averaged emissions factors for CO_2, NO_x, and SO_2 [14], hereafter referred to as “EPA Emission Factors” due to their origin in eGRID and their correspondence to the sub-regions depicted in Fig. 1. eGRID compiles the characteristics of electricity production across the entire the United States and is used for studies on reducing emissions [14].

While the method for producing these emission factors is straightforward, this means that the same emission factors are presented for all the locations in each eGRID sub-region [15]. This approach will not spatially resolve differences within a sub-region and will average the LMP dependencies across the region.

Furthermore, the data is based on data collected for the years 2005 and 2008, so although they capture diurnal and seasonal variations, these factors are not unique to a specific time period and do not necessarily represent the load pattern on any one day.

LEEM

The Locational Emissions Estimation Methodology (LEEM) was developed at Wayne State University by Carol Miller with the support of the the Great Lakes Protection Fund for the purpose of reducing harmful emissions from power plants in the Great Lakes basin [16]. This tool provides detailed temporal emission factor calculations based on locational marginal prices [10].

LEEM 2.0 utilizes the publicly published LMPs for electricity generated by the power plant portfolio in a selected eGRID region, and the demand profile is used to predict the real time (RT) or day ahead (DA) emissions factors. In LEEM 2.0, the data collection is focused within the MISO region; shown in Fig. 2. LEEM data is available in much more geographic detail at the level of the commercial pricing node (CPN) geographical detail and with a resolution of five minutes.

Fuel mix

In this work, the dynamics of temporal emission factors in the MISO region is investigated. The MISO region electricity is provided by means of coal, natural gas, nuclear, wind energy, and other renewable resources [17]. Depending on the market marginal pricing and demand profile, the portfolio of active power generators is determined. Therefore, the fuel mix associated with power generation changes with the market clearing price. This is demonstrated in Fig. 3, which shows the fuel mix portfolio for two different times in the MISO region.

Building energy modeling

Commercial building energy consumption can be modeled using EnergyPlus, which is developed and maintained by the Department of Energy (DOE) with intended applications including building energy efficiency research [16]. Energy simulations can easily be performed on generic commercial building models by taking advantage of the commercial building reference models that have been published by the DOE. For EnergyPlus simulations, a full year is selected as the simulation period and TMY3 weather data is used for the studied locations [17]. In this work, the cities of Hobart and Orleans in the state of Indiana; and Detroit and Traverse City in the state of Michigan are