DETERMINING POWER SYSTEM CAPACITY VALUE AND EMISSIONS OF STEAM-CONSTRAINED COGENERATION

By

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Highlights

- Reliability metrics to assess power system capacity value is applied to combined heat and power plants.
- Steam constraints that limit power generation can significantly reduce a combined heat and power plant's power system capacity value.
- Regional daily electric peaks may not align with combined heat and power plant steam demand, eroding the capacity value of the plant.
- An increase in steam demand during times of peak power demand on the grid can increase the power system capacity value of CHP plants.

Abstract

Combined heat and power (CHP) plants have received a resurgence of attention from power system planners and policy makers in an effort to fully realize the potential of the technology. CHP plants that are thermal-primary, however, do not always maximize the benefits provided to the power system. In this study, we examine how power system planning metrics can be applied to CHP plants to better understand the impact of steam-driven constraints. This application of these methods will allow CHP plant owners and grid operators to be better informed of the capacity value that these plants provide to the power system and identify opportunities to increase CHP contribution to resource adequacy. Using the University of Michigan's Central Power Plant as a case study, we found the effective load carrying capability (ELCC) of the plant to be 56% of its rated capacity, with the steam constraints limiting that value. We also showed that if steam demand could be increased during peak power system demand, then the capacity value of the plant would increase linearly. Currently, local steam demand is greatest during winter months while regional daily electric peaks are greatest during summer months. Alleviation of this misalignment would be necessary to increase the ELCC of the plant.

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Introduction

Cogeneration plants, which produce both useful thermal and electric energy, provide benefits to the power system that are not consistently measured or valued. Typically found in industrial, hospital, and university campuses, cogeneration plants can supply electric energy more efficiently than the surrounding regional electric grid [1,2]. If valued appropriately, these plants can provide firm generating capacity to meet peak electric loads, reducing the need for larger utility scale electric generating units. This study employs power system reliability methods to determine the system capacity value of thermal-primary cogeneration plants.

Probabilistic methods have been used by electric grid system planners for over a half century to plan for and build a generation portfolio that reliably deliver electric power to consumers [3]. As Calabrese details in [3], historical information of generators is analyzed to determine a forced outage rate of electric generator types. Assuming individual generator outages are independent, the generators' forced outage rates can be combined with an expected electric load profile to probabilistically predict the fraction of time during which a loss of load driven by insufficient generating capacity can be expected to occur in a future period. This probability calculation is a key determinant for the generation reserve capacity.

Loss of load probability (LOLP), loss of load expectation (LOLE), and effective load carrying capability (ELCC) are common reliability indices that can be used to determine the capacity value of an individual generator to the system [4]. The LOLP is the probability that load exceeds available generating capacity at a given point in time, and the LOLE is the cumulative time of such events. The ELCC is a measure of the capacity that a generator provides that reduces loss of load events in the power system. Garver describes a graphical approach that can be used to determine the ELCC of a generator given a constant system load [4]. Using this approach, the author calculated the ELCC of a 600 MW generator, demonstrating that further additions of 600 MW units to this system, effectively increasing the capacity of the system, result in larger effective capabilities for each successive unit. The study shows that the reliability target has only a minor effect on the load carrying capability.

Historically applied to fuel based electric generators, reliability indices have been more recently used to determine the capacity value of renewable generators and energy storage [5–8]. Madaeni et al. use a capacity factor-based method to approximate the capacity value of concentrating solar power plants with thermal energy storage using the 10 highest-load hours of the year in the southwestern United States [5]. They conclude that capacity payments can significantly increase available capacity as energy prices are not a perfect indicator of scarcity of supply. The marginal value of energy storage quickly tapers off after two to three hours of storage because the authors find that energy prices and LOLPs are not perfectly correlated. High energy-price hours with low LOLP exist in the period of study. During these hours the plant will sell energy, with the energy revenues outweighing capacity-related penalties if the plant cannot generate during a subsequent high-LOLP hour. This market based operational strategy and resulting capacity penalty is also noted in a study of energy storage [7]. The authors execute a similar capacity-factor based approximation study for photovoltaic solar plants in [6], and as in [5] conclude that consideration of a subset of high LOLP periods to be the closest approximation methodology to reliability-based methods.

Reliability modeling and simulation can be also be applied to distributed generation (DG). Chowdhury et al. present a reliability model to determine the DG equivalence to a distribution facility in an attempt to improve the distribution system reliability while meeting increasing customer load requirements [9].

While the study uses General Reliability's DISREL program to model the test case, the authors note that a Monte Carlo approach could also be used to determine the capacity value of the distributed generation—both fuel and renewable based.

Photovoltaic (PV) solar and battery energy storage plants can be designed to fit within the distribution network (e.g. on residential rooftops) or to be transmission tied (e.g. utility scale). Despite their unique operational constraints, the previously mentioned reliability metrics and simulation methodologies can be applied to these electric generators. U.S. grid operators utilize some mix of simulation and historical data with these reliability metrics to assign a capacity value to solar and wind on an annual basis [10–12]. In a forward looking study, Laws et al. used ELCC in a systems dynamics model to analyze the effects of residential PV adoption on utility rate structures and electric grid defection, noting the decline of the ELCC of PV systems with increased penetration of PV systems [13].

Simulation of generator availability in serving customer load can help determine future capacity requirements and the capacity value of individual generators. Billinton and Huang combine generation and load data for a system to create a risk model that is sequentially simulated, concluding that system reliability is directly related to the generating unit reliability parameter (e.g. equivalent forced outage rate demand or derated adjusted forced outage rate in the study) [14]. Similarly, Monte Carlo simulations can help system planners assess existing and future reserve margin needs, and these types of simulations have become more common place as computing power has increased [15,16]. In examining simulation results in [16], Billinton and Sankarakrishnan note, however, that if load duration curve data are available, they can be used together with generator availability to obtain reasonably accurate reliability indices for the system.

The aim of this paper is to assess the capacity value of a particular type of distributed generation—combined heat and power (CHP), also referred to as cogeneration, plants. CHP plants generate thermal energy and electricity for the heating, cooling, and electric power needs of nearby loads. The plants can be designed and operated to partially or fully meet thermal and electric power needs. Both steam boilers and steam turbines are prevalent in thermal and electric generation plant designs, and thus thermally driven CHP plants are a common design choice. Load patterns (daily, seasonal, and annual) and connectivity and use of surrounding utility services are some of the key design and operational considerations [17]. While Cho et al.'s review of one-hundred seventy articles on CHP research is a good indicator of the interest on the topic, analysis of the capacity value of cogeneration plants has been limited to date [18]. This paper examines a thermal load matching CHP plant at a university, using it as a case study to demonstrate a non-sequential Monte Carlo simulation method to determine the capacity value of a CHP plant to the power system.

Methods

Using system load and generator data, we simulated plant availability and leveraged reliability metrics to calculate the capacity credit of an electric generating plant. The intent of the analysis was to examine the impact of steam generation at a thermal-primary cogeneration plant on power system capacity value. As a case study, we modeled the ELCC of the University of Michigan's Combined Heat and Power Central Campus Power Plant (CCPP) in the Midcontinent Independent System Operator (MISO) Local Resource Zone (LRZ) 7. The University's CCPP has a nameplate capacity of 48.5 MW and 1040 klb/hr and the LRZ 7 consists of most of Michigan's Lower Peninsula. Generator characteristics and hourly load data from 2014 were gathered for LRZ 7, and CCPP electricity and steam generation were gathered for this same time period.

Reliability Metrics

LOLE measures how often a system's available capacity will fall short of system demand. Electric system planners (e.g., Independent System Operators) execute an LOLE analysis by combining load profiles and generator outages, both scheduled and forced, to determine the expected number of days in a year when a shortage may occur. The industry standard reliability metric in the United States has been a LOLE of one day, every ten years (or 0.1 days/year) [19]. The system's ability to meet this metric is based on probabilistic calculations.

As described in Milligan et al. (2016), the LOLE is defined in Equation 1:

$$LOLE = \sum_{i=1}^{n} P[C_i < L_i] \quad \text{(Eq.1)}$$

where P is the probability, C_i is the available capacity on day *i,* and L_i is the peak load on day *i* [20].

The available capacity on day *i*, C_i, is defined in Eq. 2:

$$C_i = \sum_{x=1}^{n} C_x \alpha_{xi}$$

$$\alpha_{xi} = \begin{cases} 0 \ when \ u_i \leq EFORd_x \\ 1 \ when \ u_i > EFORd_x \end{cases} \qquad \text{(Eq. 2)}$$

where C_x is the summer capacity of a single unit, *x*, $EFORd_x$ is the equivalent forced outage rate demand assigned to that unit, α_x is a binary variable that indicates the operational state of unit *x* at time *i*, and u_i is a random variable between 0 and 1. EFORd is defined as a measure of the probability that a generating unit will not be available due to forced outages or forced deratings when there is a demand on the unit to generate.

The LOLE analysis forms a basis for determining how much a generator contributes to a system planning reserve margin. One measure of an individual generator's capacity contribution is ELCC. For our study, we calculate the ELCC by determining the LOLE of the system to establish a baseline value, reducing the load by the amount that the generator supplies during that time period (e_i in Eq. 3 below), and then iteratively adding load until the LOLE matches the baseline value [7].

The calculation of the capacity value of this resource is described in Eq. 3. The incremental load value, relative to its rated capacity, is the ELCC of the generator, as shown in Eq. 4.

$$\sum_{i=1}^{n} P[(C_i + e_i) < L_i] = \sum_{i=1}^{n} P[(C_i + B) < L_i] \quad \text{(Eq. 3)}$$

$$ELCC = \frac{B}{C_A} \times 100\% \quad \text{(Eq. 4)}$$

where B is the capacity (MW) of a benchmark unit that is iteratively calculated to achieve the solution in Eq. 3. The *ELCC* is presented as the ratio of the capacity from this benchmark unit to the nameplate electric capacity of the cogeneration plant, C_A.

For thermal-primary cogeneration plants, the maximum available generating capacity of the cogeneration unit corresponding with peak load on any given day is a function of the electric power generated per unit of steam generated and the steam generated to satisfy local demand.

Case Study

The three key sets of data for this analysis include: generator information for MISO LRZ 7, an hourly load profile for LRZ 7, and historical operating data for the University of Michigan's CCPP. Geographically, MISO LRZ 7 is the majority of Michigan's Lower Peninsula (MI LP). In all cases, 2014 reported data was used.

We used the U.S. Energy Information Administration's (EIA) 860 database for generator-level data on capacity, fuel type, and technology for all generators located within LRZ 7 [21]. MISO's Historical Forecasted and Actual Load report was used to determine hourly load [22]. Because this report aggregates LRZ 2 and LRZ 7, we disaggregated LRZ 7 load using state-level retail sales from EIA-861, adjusting for nuclear, hydro, and wind generation, in addition to generation within the state that is out of LRZ 7 [23]. Michigan's CCPP records power and steam generation in 30 minute intervals. To match the hourly generation and load profiles, the two 30 minute CCPP intervals were averaged to create an hourly value.

To establish a generator profile for LRZ 7, a non-sequential Monte Carlo simulation was executed. Inputs to the simulation included the summer capacity of each generator in LRZ 7 and its EFORd, which was assigned by MISO published values for installed capacity, fuel, and technology [22]. Unplanned outages were randomly assigned and assumed to be independent of the outages occurring at other generators [24]. For a given trial, each generator was assumed to be either available up to its summer rated capacity, C_x in Eq. 2., or completely unavailable, which would occur at a frequency equal to the EFORd for the unit. Twenty-thousand trials were executed and the average of these trials was then used as the system's unforced capacity value (UCAP), which is assumed to equal C_i. Fewer than twenty-thousand trials resulted in an inconsistent generator profile and a greater number of trials offered little benefit for the larger data set.

LRZ 7 load and generator data were used with Eq. 1 to calculate the baseline LOLE for our defined system. We then used Eq. 3 and 4 to calculate the capacity value and ELCC of the Michigan Central Power Plant in LRZ 7.

Results

Local Resource Zone 7 Loss of Load Expectation Baseline

Using the described LOLE methods, the baseline LOLE of the system was calculated to be 0.0771%. Fig. 1a shows what the probability of load and generation is for a given value of power (MW). The highlighted area in Fig. 1a shows the range of load and generation where cumulative probability of a loss of load is at its highest. It is also the interval that contributes proportionally more to the LOLE. Fig. 1b shows this interval in greater detail.

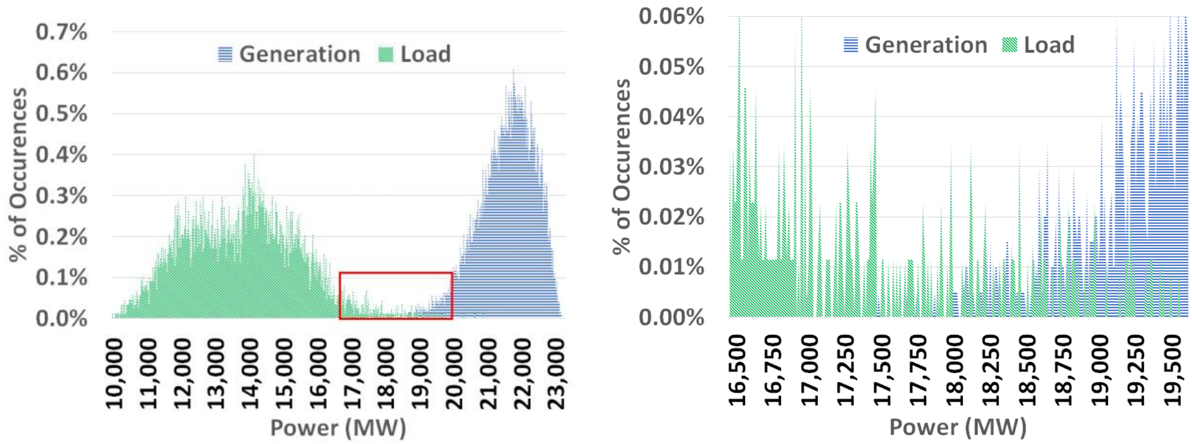

Fig. 1. Generation and load probability at a given power for (a) Local Resource Zone 7 (b) subset of Local Resource Zone 7

Steam Constraint

Steam powered generators constitute the majority of the CCPP's electric nameplate capacity. These generators source steam from onsite boilers, and the generator exhaust steam is sent to the campus to meet thermal energy load. The electric steam generators can also be bypassed to just send steam to campus. If, however, there is not sufficient steam load, the 38.5 MW electric steam generators will operate below capacity. The CCPP also has two 5 MW natural gas turbines with heat recovery steam generators. The CCPP can buy electricity from the utility serving the region (DTE Energy) to meet campus demand, but it does not sell excess electricity to the grid because the revenue does not exceed the costs under its current utility tariff.

The daily hourly peak load for LRZ 7 was determined for each day in 2014. The CCPP power and steam generation for each of those hours was then determined. The daily peak load and coincident CCPP power generation is shown in Fig. 2.

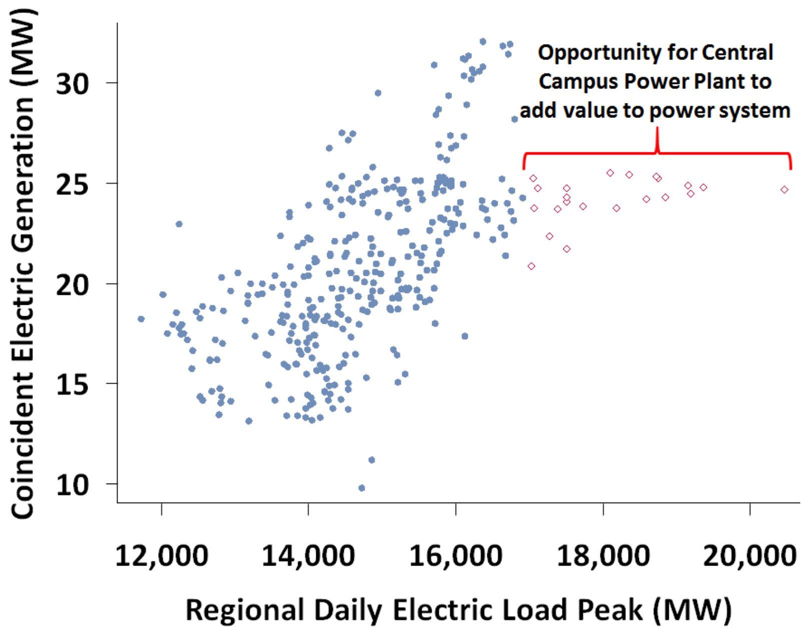

Fig. 2. Local Resource Zone 7 load and Central Campus Power Plant coincident generation peaks (daily in 2014)

For the highest power system peak load days of the year, we see that the CCPP does not generate power at its full capability. This is driven by an insufficient demand for steam. Due to this steam constraint, the CCPP is producing less power at a time when power produced is most valuable to the LRZ 7 system.

Fig. 3 shows the hourly power and steam generation at the CCPP in 2014. We see a positive linear trend between the CCPP power output and steam demand, with a general range of power that can be produced for each unit of steam demand. Examining this range, we can determine the maximum power produced for a given amount of steam as determined by physical constraints and economic constraints on operation.

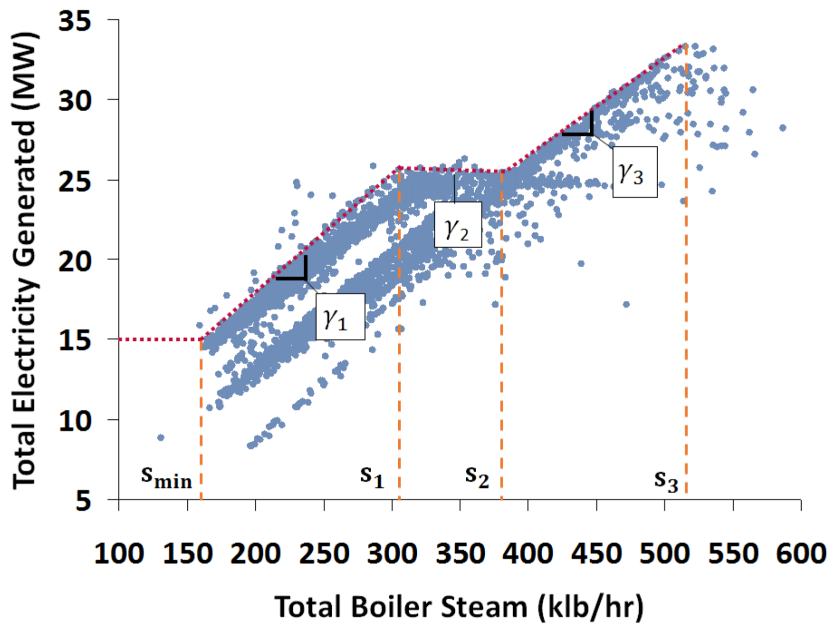

Fig. 3. Central Campus Power Plant power and steam generated in 2014 (hourly)

Effective Load Carrying Capability of Central Campus Power Plant

The baseline LOLE for LRZ 7 (0.0771%) and Eq. 3 and 4 were used to calculate the ELCC of the CCPP in 2014. We reduced the daily peak power system load by the amount that the CCPP generated during that peak time, and then iteratively added load until the LOLE matched the baseline value. This showed the relationship between steam demand and maximum generation as a constraint that may reduce the plant's power system capacity benefits. The resulting capacity credit for the CCPP was 26 MW, which is 56% of its nameplate capacity.

Steam Constraint Scenarios

To realize the full efficiency of combined heat and power, a thermal-primary cogeneration plant requires a steam load to turn the turbines that produce electricity. To model the potential power generation of the CCPP, data for steam and power generation in 2014 was used to derive Eq. 5 for the maximum potential generation subject to steam demand constraints of operation:

$$e_i = 15\,MW + \beta \quad \text{(Eq. 5)}$$

$$\beta = \begin{cases} 0 \ at \ s_{min} \\ \gamma_1(s - s_{min}) \ for \ s_{min} \ to \ s_1 \\ \gamma_1(s_1 - s_{min}) + \gamma_2(s - s_1) \ for \ s_1 \ to \ s_2 \\ \gamma_1(s_1 - s_{min}) + \gamma_2(s_2 - s_1) + \gamma_3(s - s_2) for \ s_2 \ to \ s_3 \end{cases} \quad \text{(Eq. 5)}$$

where e_i and β is measured in MW, steam is s measured in kilopounds per hour, and γ is the slope of the maximum potential generation subject to steam demand constraints of operation of the CCPP. This equation is also shown visually in Fig. 3, representing a linear fit of the steam-to-electricity generated.

With this equation, scenarios were modeled to determine the ELCC of the CCPP at 60%-180% of its actual steam operation (the nameplate capacity was used for the upper constraint). For each of these scenarios the previously mentioned LOLE and ELCC approach was used.

Fig. 4 shows the results of this scenario analysis. The capacity credit was constant for 160-170% of its actual operations. This indicates that the additional available capacity for this range would not actually reduce the LOLE of LRZ 7. The capacity credit declined a small amount (2%) between 90 and 110% of plant steam operation. For the rest of the range considered, we see a positive, nearly linear relationship between the steam output and the capacity credit value.

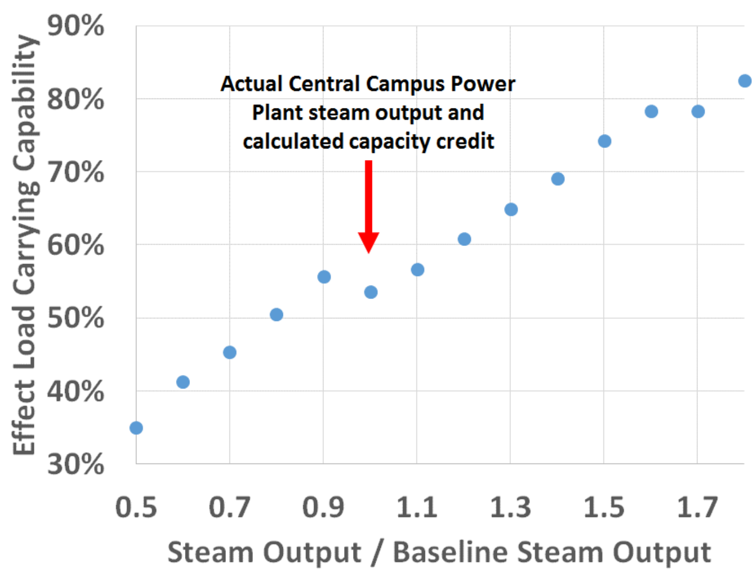

Fig. 4. Central Campus Power Plant capacity credit and steam operation

Role of Temperature

By examining the regional hourly electric peak load with the coincident CCPP steam demand and the ambient temperature, we can illustrate a relationship between the three. As shown in Fig. 5, we see that, not surprisingly, regional hourly electric peak loads are the greatest during high temperature hours. Following similar logic, CCPP steam demand is the greatest when ambient air temperature hours are the lowest in a given year. Regional electric load peaks and CCPP steam demand peaks are thus misaligned and occur at the two ends of the regional temperate range.

For example, during the 2014 regional electric load peak the CCPP ambient temperature was 29°C. The coincident CCPP steam demand was 64% of its annual daily demand peak, which occurred when the temperature was -18°C. Fazekas et al. find a similar relationship between CHP output and ambient temperature in their CHP study [25].

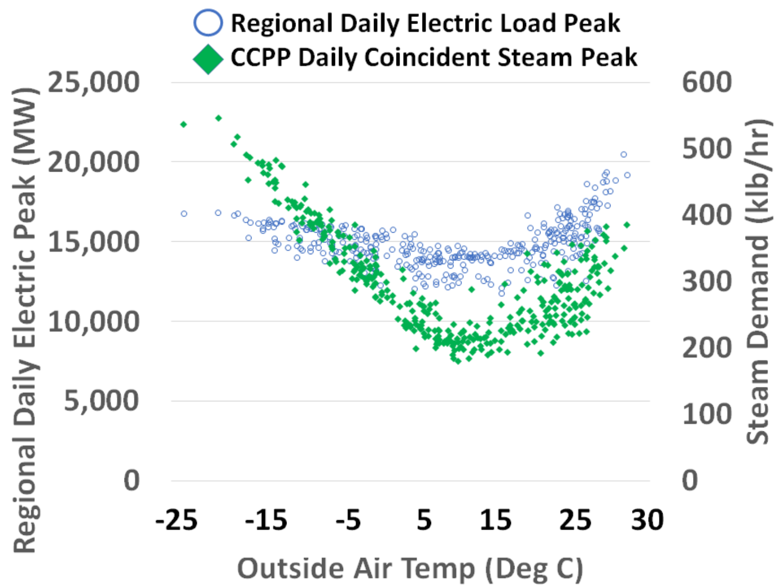

Fig. 5. Local Resource Zone 7 daily peak and Central Campus Power Plant steam demand

Steam use for cooling and emissions reductions

Regional electric load peaks and CCPP steam demand could be better aligned if the steam were used for cooling of local buildings. Understanding that this would increase the capacity value of the CCPP, we also wanted to analyze the difference in emissions of the regional power system for such a change. To do so, we used Eq. 5 to model an increase in steam demand and the associated power generation from that steam. For months in which we would expect a cooling load, June through September in Michigan, we assumed the additional steam generated would cool buildings through the use of an absorption chiller, replacing electric air conditioning in buildings. Existing infrastructure could be leveraged for this change in cooling.

The change in emissions were calculated in two parts. First, we calculated the additional emissions resulting from increased generation at the CCPP. Second, we used the Environmental Protection Agency's Avert model to calculate the reduction in regional power system emissions, which were a result of decreased electric load at central campus buildings. As an example, a 50% increase in steam load at the CCPP would result in an additional 34,389 tons of CO_2, 367 pounds of NO_x, and 344 pounds of SO_2. This same increase at the CCPP would result in a reduction of 69,900 tons of CO_2, 131,600 pounds of NO_x, and 326,400 pounds of SO_2 in the regional power system. Combining these results we would expect a regional net reduction of 35,511 tons CO_2, 131,233 pounds of NO_x, and 326,056 pounds of SO_2 for a 50% increase in steam load at the CCPP.

Discussion

The misalignment of regional electric demand and local steam demand in our case study resulted in the CCPP operating below its rated capacity during the times of greatest power system need. If the CCPP's steam demand was higher during periods of regional electric load peaks, it could produce additional electricity that would satisfy local electric demands and reduce the LOLP of the regional electric system. Currently, cogeneration units are not always incentivized to provide maximum power system benefits.

A greater understanding of the campus building energy needs is required to determine how much the CCPP steam demand could be increased. Opportunities for replacing electric heating and cooling with steam in campus buildings would be guiding factors in determining how much the CCPP capacity factor could be increased. For example, using absorption chillers that source steam from the CCPP for cooling instead of electricity sourced from the regional grid for air-conditioning units could increase CCPP utilization during peak loads in summer months and therefore provide additional power system capacity benefits. This approach would require coordinated planning for building HVAC and CCPP operations.

Utility tariff structures also influence the capacity factor of CHP plants. CHP plant owners are often required to pay a demand charge to the regional utility for continued service in the event of an unplanned plant outage. These demand charges can be large enough to affect CHP plant operations. Perea et al. describe the use of an optimization algorithm to dispatch a CHP unit with thermal storage and a boiler for building energy cost savings, taking into consideration the electric tariff for the building [26]. Gimelli and Muccillo execute a similar optimization analysis for cogeneration use in hospitals [27]. Related, Ghadimi et. al. simulate the benefits of integrated system sizing and operational strategies for CHP plants, applying the methodology to a pharmaceutical manufacturing plant [28]. Our methods could be used to redesign utility tariff structures for CHP plants. The utility demand charge assessed to the plant could be tied to the regional capacity value of the CHP plant. Continued service charges would then be better aligned with actual CHP plant operations and the electric generation capacity needed to meet service territory reliability.

Depending on the regional electric grid mix, increased CHP utilization could also result in reduced emissions resulting from electricity generation. Kikuchi et al. examine the use of and effectiveness of distributed CHP in reducing greenhouse gas (GHG) emissions [29]. Similarly, Howard and Modi ascertain the effects of building type, building size, climate and current GHG emissions from grid electricity on the GHG emission reductions possible from natural gas fueled CHP systems [30]. When GHG emissions from grid electricity are low, there must be a concurrent thermal demand in sufficient magnitude to achieve GHG emissions reductions. Future research could include further analysis of the potential to reduce regional emissions attributable to electric generating units from increased utilization of existing thermal-primary cogeneration plants.

Conclusions

Using a case study, we showed how a Monte Carlo simulation and industry standard reliability metrics can be used to assess the power system capacity value of a CHP plant. If the CHP plant is thermally driven, as the CCPP is, then steam constraints can reduce the power system capacity benefits of the plant as measured by ELCC. We showed, however, that if this steam constraint could be relaxed, then the ELCC can be increased. To do so would likely require integrated planning of building heating and cooling loads to fully utilize the available steam capacity. Any prohibitive utility tariff structures would also have to be changed to remove any economic constraints.

Areas of further analysis could include the potential to reduce regional emissions attributable to electric generating units from increased utilization of existing thermal-primary cogeneration plants. While CHP plants still utilize carbon based fuels to generate electricity and heat, the high fuel efficiency of CHP plants can reduce the total amount of fuel required compared to sourcing the same amount of energy from the regional electric grid. Emissions from electric generating units do vary by region, so we would expect the emissions reductions to vary accordingly.

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