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Assessing the impacts of droughts and heat waves at thermoelectric power plants in the United States using integrated regression, thermodynamic, and climate models



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ABSTRACT

Recent droughts and heat waves have revealed the vulnerability of some power plants to effects from higher temperature intake water for cooling. In this evaluation, we develop a methodology for predicting whether power plants are at risk of violating thermal pollution limits. We begin by developing a regression model of average monthly intake temperatures for open loop and recirculating cooling pond systems. We then integrate that information into a thermodynamic model of energy flows within each power plant to determine the change in cooling water temperature that occurs at each plant and the relationship of that water temperature to other plants in the river system. We use these models together with climate change models to estimate the monthly effluent temperature at twenty-six power plants in the Upper Mississippi River Basin and Texas between 2015 and 2035 to predict which ones are at risk of reaching thermal pollution limits. The intake model shows that two plants could face elevated intake temperatures between 2015 and 2035 compared to the 2010–2013 baseline. In general, a rise in ambient cooling water temperature of 1 °C could cause a drop in power output of 0.15%–0.5%. The energy balance shows that twelve plants might exceed state summer effluent limits.

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1. Introduction

Power plants withdraw a significant amount of water – about 45% of total fresh and saline water withdrawals in the country in 2010 – to cool steam used to generate electricity (Maupin et al., 0000). At the same time, ongoing drought has revealed the vulnerability of thermoelectric power plants to the risks of low water levels and high water temperatures. High temperatures can cause the cooling process to become less efficient. In general, a rise in ambient cooling water temperature of 1 °C could cause a drop in power output of 0.15–0.5% (Asian Development Bank, 2012; Linnerud et al., 2011).

In an open-loop or recirculating cooling power plant with a cooling pond, the relationship between a power plant's efficiency,

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thermal loading, and cooling water characteristics are determined by thermodynamic principles. As water passes through the power plant, heat is lost to the air or transferred to the cooling water and into the pond, river, or lake as the water is discharged. For the plant to condense the same amount of steam in the cooling process when the intake water temperatures are higher, it needs to withdraw water at higher rates, heat the withdrawn water to higher temperatures, or both. If the power plant is at risk of violating its thermal water discharge limits in its environmental permit, the net power generation can be reduced as a way to lower discharge temperatures. This risk to loss of generation is important because it affects the reliability of the power system and puts human lives at risk. This risk can be exacerbated in the future, as decisions are made today about long-lived capital assets that might be operating under different climatic conditions in the future. Therefore, analysis and methods presented in this paper can be used to inform those decisions with the intent of improving the reliability of current and future power sector.

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1.1. Power plant cooling

Thermoelectric power plants generally require water as the working fluid as part of the steam cycle that is used to generate power (Moran and Shapiro, 2004). However, the largest demand for water in thermoelectric plants is for the cooling water used in condensing the steam back into a usable working fluid (Wagman, 2013). Several types of cooling are used. The most common types are once-through and recirculating cooling. Once-through plants withdraw large amounts of water from rivers, lakes, ponds, and groundwater wells and pass it through tubes of a condenser to cool the steam as it exits the turbine. The steam is then returned to the boiler as liquid water for use again. The cooling water then returns to the environment at an elevated temperature (Moran and Shapiro, 2004). Wet-recirculating systems use cooling towers or cooling ponds to dissipate heat from cooling water to the atmosphere, reusing the cooling water multiple times in the process (Mittal and Gaffigan, 2009). This study examines oncethrough and recirculating cooling plants with cooling ponds because these plants return cooling water to the environment at elevated temperatures.

1.2. Previous research on water constraints for power plants

In recent years, there have been many assessments of water use for power as well as advancements in evaluating the impacts of water stress and increased energy and water demand on the power sector (Yan et al., 2013; Koch and Vogele, 2009; Miara and Vorosmarty, 2013; Stillwell et al., 2011; Roy et al., 2012; Sovacool and Sovacool, 2009; Chandel et al., 2011; Harto et al., 0000; Fthenakis and Kim, 2010; Feeley et al., 2008; Vassolo and Doll, 2005). Given that climate projections estimate higher air temperatures for the United States in future years (PNNL, 0000; IPCC, 0000), many of these assessments seek to evaluate the power plant productivity in the face of low water levels or high air or water temperatures (Yan et al., 2013; Scanlon et al., 2013). A National Energy Technology Laboratory report found that most cases of de-rating or shutdown were not associated with low water levels at the intake but rather elevated temperatures of effluent or at cooling water intakes (NETL, 2010). Miara and Vorosmarty model power plant thermal discharges into riverine systems in the Northeastern US (Miara and Vorosmarty, 2013). While the work presented here is similar to Miara and Vorosmarty in seeking to characterize impacts of discharges into a large riverine system as well as cooling ponds, the analysis in this manuscript is taken at a screening level and includes a thermodynamic model of the power plant itself with the intent of informing decisions in the power sector. By contrast, the study by Miara and Vorosmarty includes much more hydrological detail to quantify impacts on the water systems.

Many studies have assessed the impacts of low water levels, but few have attempted to quantify the vulnerability power plants face of reduced generation associated with higher cooling water temperatures. Building on past research in the field (Yan et al., 2013; Koch and Vogele, 2009; Miara and Vorosmarty, 2013; Stillwell et al., 2011; Roy et al., 2012; Sovacool and Sovacool, 2009; Chandel et al., 2011; Harto et al., 0000; Scanlon et al., 2013; Cook et al., 2013, 2014; Sanders, 2015) as well as work in surface water temperature modeling (Segura et al., 2015; Webb et al., 2008; Komatsua et al., 2007; Stefan et al., 1993; Webb and Walling, 1993; Erickson and Stefan, 1996; Webb and Nobilis, 1997; Pilgrim et al., 1998; Ozaki et al., 2003; Ducharne, 2008; Caldwell et al., 2014), this research seeks to fill the gap in knowledge of the magnitude of influence that higher temperatures will have on power plant effluent water temperatures to quantify a power plant's exposure to risk of de-rating induced by warm cooling water in future decades. This study assesses the effect of meteorological parameters and heat dissipated from power plant cooling to determine the change in water temperature at various power plants in the Upper Mississippi River Basin (UMRB) and the Gulf Coast Basin (GCB) by employing multiple linear regression and energy balances and taking into account the effect the performance of a neighboring upstream plant could have on downstream plants. The risk of reduced operations is assessed through estimation of intake and effluent water temperatures over the next 1–2 decades and comparison to current restrictions.

2. Material and methods

To analyze the risk of power plant curtailment due to high effluent discharge temperatures, a multiple linear regression model for intake cooling water temperature in combination with an energy balance of the power plant is utilized to estimate the historical cooling water effluent temperatures (T_{eff}) at power plants in the UMRB and GCB. This model is executed for power plants that reported discharge temperatures and utilized an open loop or recirculating cooling pond system. The model employs proxies for the influence of cooling water intake temperature and heat dissipated in electricity generation, the details of which are explained below.

2.1. Calculation of intake temperature via multiple linear regression

Past research in modeling monthly surface water temperature has indicated a correlation between air temperature and surface water temperature in streams and lakes (Segura et al., 2015; Webb et al., 2008; Webb and Walling, 1993; Erickson and Stefan, 1996; Webb and Nobilis, 1997; Pilgrim et al., 1998; Ozaki et al., 2003; Ducharne, 2008; Caldwell et al., 2014). Segura et al. reviewed nineteen stream water temperature models conducted between 1982 and 2014, sixteen of which employed linear or combined linear/logistic models for water temperature (Segura et al., 2015).

In this study, we use a multiple regression model to estimate monthly average cooling water intake temperature at month, t, with ambient dry bulb air temperature ($T_{DB}(t)$ (°C)), dew point $(T_{DP}(t) (^{\circ}C))$, intake temperature of the previous month $(T_{in}(t - T_{in}(t)))$ 1) (°C)), average wind speed for the month (V(t) (m/s)), and temperature of the cooling water discharged from the upstream plant $(T_{up}(t) (^{\circ}C))$. Note that t represents the time in months while the *t*-test is a hypothesis test. A regression is employed based on characteristics of the environment around each power plant and historical data from 2010–2013 to determine the five parameter coefficients, $\beta_1 - \beta_5$, and constant β_0 . The resulting model for estimated power plant cooling water intake temperature, $T_{in}(t)$, is shown in Eq. (1). While the equation is the same for each power plant, the estimates for $\beta_0 - \beta_5$ are specific to each power plant tested. The illustration in Fig. 1 shows the relationship between $T_{in}(t)$, $T_{up}(t)$, and the plant's effluent temperatures, $T_{eff}(t)$.

$$T_{in}(t) = \beta_5 T_{DB}(t) + \beta_4 V(t) + \beta_3 T_{DP}(t) + \beta_2 T_{in}(t-1) + \beta_1 T_{up}(t) + \beta_0.$$
(1)

Argonne and PNNL used weather station data to calculate historical average monthly air temperature, dew point, and wind speed used in Eq. (1). The average values for each month were calculated based on interpolated daily values measured by National Oceanic and Atmospheric Administration climate stations. The interpolation was done using a quadrat method, where daily climate data were aggregated first to a grid of points across the entire basin (known as a HUC2), then grid point daily values were aggregated by weighted average to subbasins (known as HUC8 subbasins). Once Grid Cell daily values were interpolated, daily data was then combined to HUC8 scale using a weighted Download English Version:

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