On Modeling the Dependency of Renewable Infeed and Demand Response Capacity

Raksha Ramakrishna, Kári Hreinsson and Anna Scaglione

It is well understood that temperatures affect energy consumption, with regions utilizing electricity for heating and/or cooling observing considerable seasonalities in load, largely attributed to thermal load demand fluctuating with changes in outdoor temperature. Past work shows that the contribution of thermostatically controlled loads (TCL) grows roughly proportionally to the difference between actual outside and desired indoor temperatures. Utilizing these models for California as an example, along with surveys and temperature readings, we disaggregated the California Independent System Operator (CAISO) load signal to extract the air conditioning contribution as depicted by Fig. 1. More specifically, to calculate the TCL load contribution, each customer profile c on sample day d at time-of-day k is modeled as:

$$p^c_d[n] = a^c(\tau_d[n] - \theta^c_{\mathrm{r}}[n])^+ + e^c_2[n]. \tag{1}$$

where $\theta^c_{\mathrm{r}}[n]$ is the time-varying reference temperature (constant in a season and time of day), a^c is a function of thermal parameters of the TCL installation, $\tau_d[n]$ is the outside temperature, $e_2[n]$ is modeling error and $(x)^+ = \max(0, x)$. Naturally, solar irradiation affects both temperature as well as solar power production, making the two statistically dependent as captured in the *Bayesian graphical model* in Fig. 2. These underlying dependencies are not completely ignored in traditional power systems operations, as most load forecasts use temperature forecasts as an input. However, the literature on probabilistic forecasts that explicitly deals with these issues is scarce. What motivates our work are two basic questions: *"Does it make sense to ignore these dependencies in a stochastic optimization framework?"* and *"How can one account for them in the decision model?"* We would like to argue that is inherently inefficient (i.e. it leads to higher complexity and more conservative solutions for the same level of representation accuracy) to make decisions based on the assumption that renewable power production from solar installations and thermal load are independent processes. Capturing this dependency is important because thermal loads such as air conditioners, heat pumps, space and water heaters, are excellent candidates for providing demand response (DR). The post will show that these probabilistic models can be used to commit more efficiently DR reserves to overcome the different possible scenarios of solar power production over a future horizon by varying the DR capacity for each solar PV scenario. Although this basic notion is more general, the simple model we will use to represent such a dependency is shown in Fig. 3. The portion capturing the TCL to temperature dependency (used in Fig. 1) is the same as in (1). The ability of a Volterra based non-linear model in Fig. 3 to capture the temperature to solar pv power dependency is illustrated in Fig. 4.

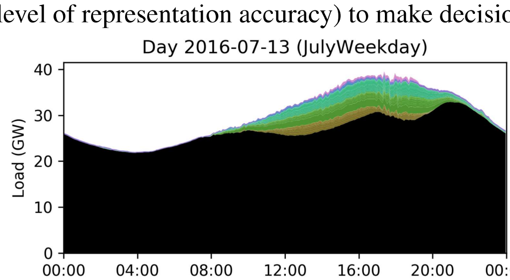

Figure 1: *Disaggregated CAISO load for a Wednesday in July. Colored region shows what part of the load can be attributed to residential air conditioning, while the black portion denotes other load. The different colors represent different populations air-conditioners with thermal parameters from existing surveys.*

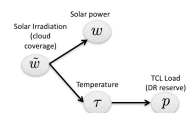

Figure 2: *Bayesian network of the time series of solar irradiation ($\tilde{w}$), solar power data (w), temperature (τ) and TCL load (p).*

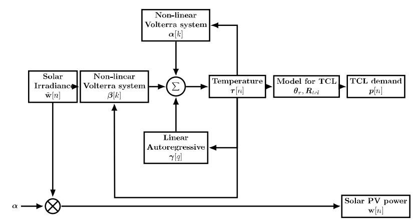

Figure 3: *Model for the statistical dependence between temperature, solar power and TCL load The DR capacity dependence will be presented in the poster.*

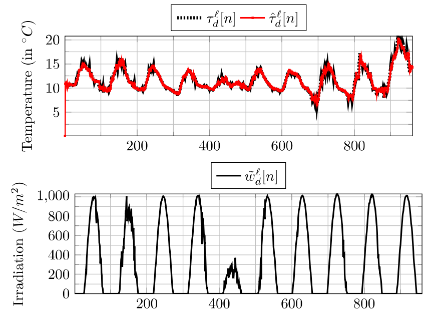

Figure 4: *Deriving temperature (bottom) from irradiation (top) using Fig. 3.*