NET LOAD ERROR: WHAT IS A GOOD LOAD FORECAST?

Nikolaus HOUBEN*[1], Amela AJANOVIC[1], Hans AUER[1], Reinhard HAAS[1]

Overview

As we transition towards a decarbonized economy, the integration of variable renewable energy resources (VRE) and sector-coupling into the electricity grid places unprecedented pressure on grid operators to effectively forecast and curb peak load. Today there exists a plethora of load forecasting methods, ranging from simple heuristics to advanced machine learning algorithms that can be used for this task. When selecting a suitable method, practitioners often look to conventional Euclidian error metrics, such as the root-mean-squared error (RMSE). However, these metrics are not motivated by real operational requirements in electricity grids. Furthermore, they exhibit what has been referred to as the "double penalty effect" (see [1]). This effect occurs when a forecast of a peak is correct in terms of intensity, size, and timing, but incorrect exact location. For an example consider Figure 1, where (a) shows an informative, but erroneous forecast, while the more accurate (b) is a constant line and thus uninformative for grid operators.

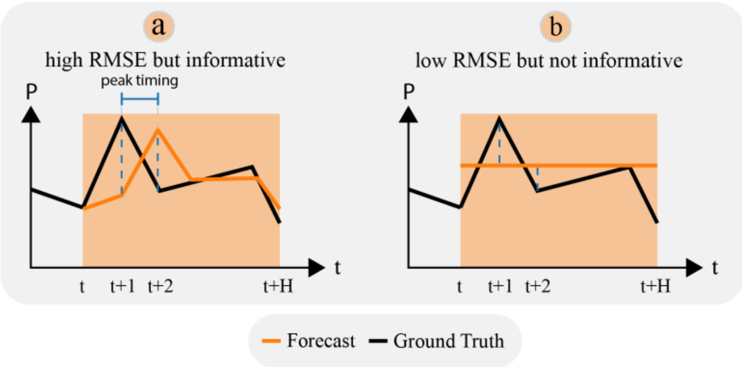

Figure 1: Double Penalty Effect of Euclidian Performance Metrics

Moreover, in a recent review article on low-voltage load forecasting Haben et al. [2] remark that: "there are very few examples of the impact and role the forecast's accuracy has on the outputs of the application." With this work we hope to contribute to closing this research gap, by presenting an application-driven error metric that evaluates forecasts based their ability capture peak load. As reducing peak load is a global objective in electricity grids, and increasingly trickles down to consumers through demand charges, the methods presented here cater to all those asking themselves if their load forecasting method would in fact be useful in a real energy system application.

Methods

Consider a load timeseries y_t and a forecast $\hat{y}_{j=1:H;t}$ $\forall t \in T$. We propose the Net Load Error (NLE), which evaluates an ex-post operational cost C^{opr} attributed to the maximum net load $\boldsymbol{l_t}$ against a daily demand charge P_{DC}:

$$C^{opr} = \sum_{d} \max l_{t;d} * P_{DC}$$

The net load results from operating a battery electric storage system (BESS) through Model Predictive Control (MPC). Specifically, by charging the BESS with charging action u_t, the real load y_t can be modified resulting in the net load l_t as given by:

$$l_t = y_t + u_t$$

To understand how the charging action u_t is found, examine the stylized energy system in Figure 2(a), which at timestep *t* consists of a scaled real load (black) $\boldsymbol{y_{j=1:H;t}}$, its scaled forecast (orange) $\boldsymbol{\hat{y}_{j=1:H;t}}$, a

[1] Energy Economics Group, TU Wien, Gusshausstraße 25-29 E370-03, 1040, Wien;
Tel.: +43 6641545107;

BESS with parameters $\boldsymbol{\theta}$. To achieve peak load reduction an optimizer minimizes the following optimization problem at each timestep *t*, by finding charging actions u ($\boldsymbol{u}_{j=1:H;t}$):

$$\min_u C = \min_u (p^h + V(\theta)) \qquad \text{s.t.} \qquad g(u, P_{DC}, \theta) \geq 0 \,;\, h(u, P_{DC}, \theta) = 0$$

The horizon peak p^h is the highest net load value within the horizon *H*. V(.) is a terminal cost term, quantifying the value of stored energy at the final timestep j=H in the optimization. This term ensures that the BESS is not fully discharged at the end of each optimization. The constraints *g* and *h* incorporate the linearized BESS dynamics, as well as the horizon peak.

Moving on to Figure 2(b), the usual MPC formulation prescribes the first charging action from the optimization at timestep *t* be applied to the real system at the next timestep *t+1;* $l_{t+1}^{opr} = y_t + u_{j=1;t}$. Consequentially, the state-of-charge (SOC) is updated; $SOC_{j=0;t+1} = SOC_{j=1;t}$.

The key insight of the NLE is that a charging action based on an erroneous forecast leads to a sub-optimal net load, as shown in Figure 2(b), where the operational peak is greater than the optimally planned one. Repeating this for all timesteps *t*, as shown in Figure 2(c), once with the forecast as the input to the optimizations and once with the ground truth (perfect forecasts), a cost difference can be evaluated (see Figure 2(d)), which we refer to as the NLE.

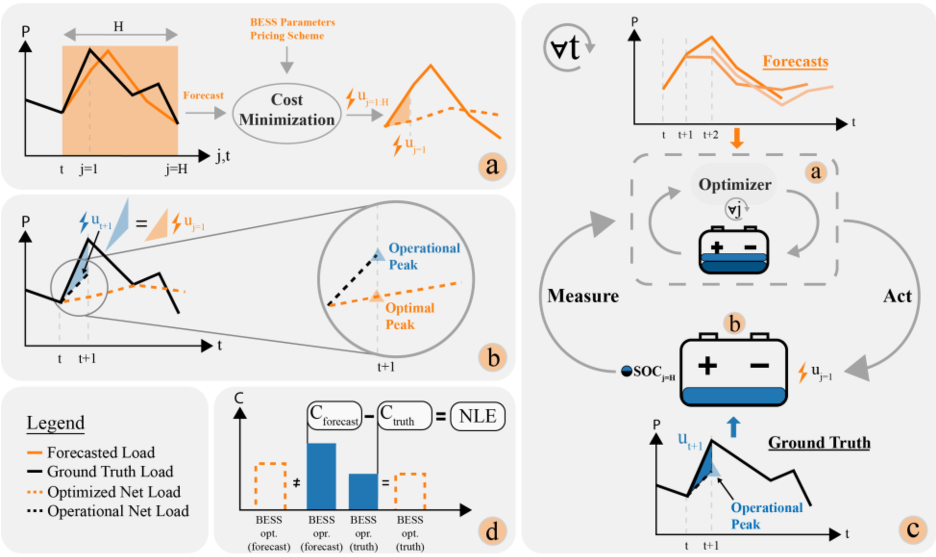

Figure 2: Net Load Error Framework

Results

We evaluate the NLE and RMSE on forecasts of 6 machine learning forecasting models on an open-source Los Angeles county-level electricity load dataset [3]. Results show the expressivity of such the proposed metric and demonstrate the importance of considering load forecasts in the context of real energy applications.

References

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