FORECASTING LOAD AND RENEWABLE GENERATION FOR DISTRIBUTION NETWORKS

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ABSTRACT

Day ahead hourly forecasting is discussed in this paper. Two classes of forecasting schemes are considered for distribution systems. The first scheme is based on disaggregation of utility level forecast while the second scheme takes the load (or generation) history and the weather history at any node and uses multi-linear weighted regression on a suitable neighborhood for forecasting. This regression based scheme is compared with a profile based scheme and is shown to reduce forecasting error by 50% on sample data.

Introduction

Traditionally, utilities focus on accurate utility-wide load forecasts. This helps them plan generation and acquire power from the grid to satisfy excess load in a timely fashion, thus optimizing costs. By distribution level forecast, we mean a load (or renewable generation) forecast for every node in the distribution system. Interest in distribution level forecasts is growing recently because of its use in network management, i.e., scheduled maintenance, network reconfiguration and dealing with unplanned disruptions.

Two distribution network forecasting schemes are considered in this paper – top-down and bottom-up. We assume tree structured distribution networks prevalent in North America. In the top-down scheme, we take the utility-wide forecast and disaggregate it down the distribution network based on (time-varying) load factors. These load factors themselves are estimated via a regression model. This process yields forecasts at each node of the distribution network.

In the bottom-up scheme, we take the load (or generation) history along with the corresponding weather history at each terminal node of the network, and use it to forecast the load at that node. Then we aggregate these forecasts up the distribution network tree to obtain forecasts at all intermediate nodes. Note that if history at an intermediate node is available, which is often the case for substations, then a forecast can be directly computed for that node using regression.

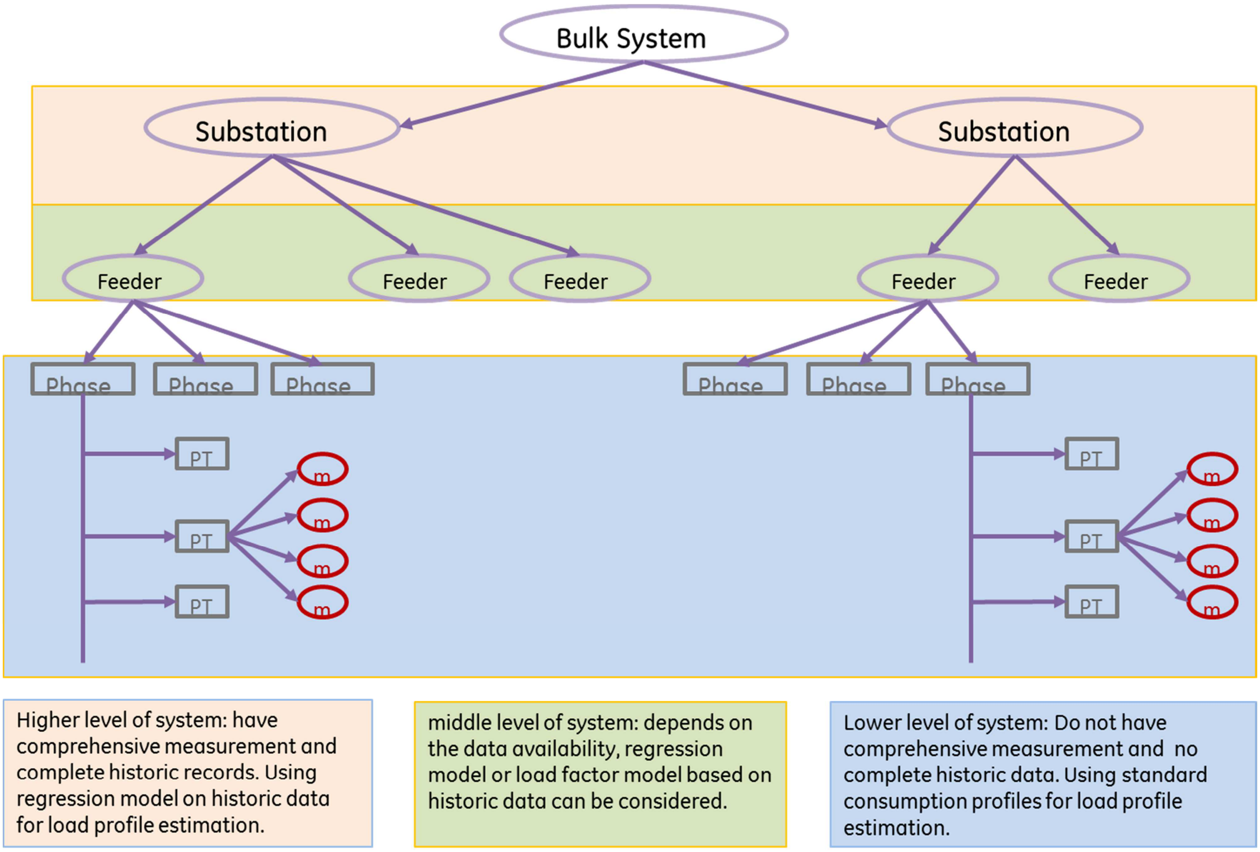

Figure 1: Schematic overview of a utility distribution network

Finally, we apply the regression method of the bottom-up approach to a single node in a real network and show that it reduces forecast error by approximately 50% over conventional profile based forecasting methods.

Weighted Local Multi-Linear Regression

Consider a particular node in the distribution network. Let w(d,h) denote a row vector of weather parameters for day d and hour h at that node. (These parameters may include temperature, humidity, pressure, irradiance, wind speed, etc.)

Let l(d,h) be the actual load (or generation) at the selected node on day d at hour h.

Next, we describe how to construct a forecast for tomorrow. Suppose tomorrow's weather forecast for hour h is wf(t,h). For a pre-specified integer n, determine n weather points from the history w(d,h) that are closest to wf(t,h) in some pre-specified measure. Let these points be $w(d_1,h)$, $w(d_2,h)$, …, $w(d_n,h)$.

Suppose we assign weight u_i to the point $w(d_i,h)$, and U be the diagonal matrix with i-th diagonal entry given by u_i. Define W to be the matrix with i-th row given by $w(d_i,h)$. Define b to be the column vector of regression coefficients and l to be the column vector with i-th component given by $l(d_i,h)$. Then b is given by:

$$b = (W^T U^{-1} W)^{-1} W^T U^{-1} l$$

The forecast load lf(t,h) for tomorrow at hour h is given by wf(t,h)b.

Often, the first component of the vector w is set to one to allow for an intercept in the forecast load.

In this work, we always choose $u_i = 1$.

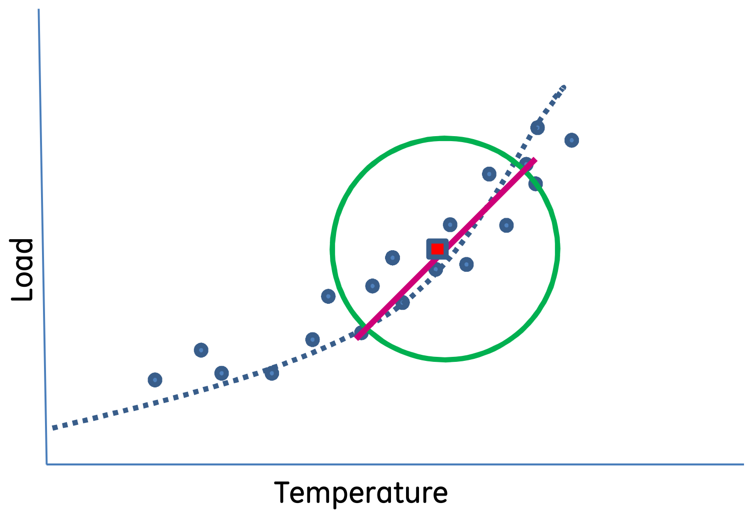

Figure 2: Dynamic linear regression using nearest neighbors

Forecasting the Load Factor

Suppose a node n in the distribution network has children c_1, c_2, … , c_k. At hour h of day d, the weather is w(d,h), and the load at c_i is l_i. Then the load factor for node c_i on day d at hour h is given by:

$f(c_i, d, h) = l_i / (l_1 + l_2 + … + l_k)$.

Suppose you are given $f(c_i, d, h)$ for all previous d and h. Then, given the weather history, one can use the weighted local multi-linear regression to forecast the load factor (instead of the load) for tomorrow at hour h for node ci.

Alternate Calculation of Load Factor

The previous calculation of the load factor assumed availability of meter readings l_1, l_2, …, l_k. What if these readings are not available? In this case, one can disaggregate the forecast z for node n using load profiles of end customers under each node c_i.

Specifically, redefine l_i by the sum of load profiles (for the specified hour h) of all the end customers under the node c_i. Then

f(ci, d, h) = z * li / (l1 + l2 + … + lk).

Top-down Forecasting: Disaggregation

Top-down forecasting works as follows: we start with the utility-wide forecast at the utility root node, and use load factors to forecast load at the children of the utility node. The same process is repeated at the children of the utility node, and then further down the tree until we have a forecast for each customer node. In this scheme, the load factors at any node may be computed by either of the two methods described above.

Bottom-up Forecasting: Aggregation

This load forecasting scheme assumes that meter reading history is available for every end customer. We use weighted local regression to forecast the load at every end customer. These forecasts are then added up the distribution network tree to obtain forecast for each interior node.

If we use this scheme to forecast renewable generation, then the assumption is that the meter history is available for every renewable source.

Weighted Local Regression Forecast: A Real World Example

Historical data for a complete utility network is very expensive to collect and maintain. Even if this history were available, periodic network reconfigurations must be factored out to obtain meaningful prediction for internal (i.e., non-end user) nodes of the network. For these reasons, testing our prediction scheme on a complete network is not feasible at this time.

However, we have been able to validate the forecast for a single end-user node as follows. We obtained the historical load data for an end-user from a utility. The utility currently forecasts this single user load based on its seasonal profile, irrespective of the weather forecast. We use this profile based forecast as the benchmark to compare against.

First, we augment the load data with the temperature data. This gives us both historical load and temperature data. Then we use tomorrow's temperature and the weighted local regression to obtain a forecast for tomorrow's load. This is our forecast for the load. Next, we compare both the above forecasts – the profile based forecast and our forecast – with the actual load tomorrow. The results showed that our forecasting approach reduced the average hourly forecasting error from about 16% down to 8%.

Conclusion

We have developed a weather incorporating regression based forecasting model to forecast load and renewable generation at each node in a utility's distribution network. We tested this model on some real data and were able to reduce the average hourly error by half.