Smard Grid Software Applications for Distribution Network Load Forecasting

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***Abstract* — This paper describes three software applications for distribution network load forecasting in a Smart Grid environment: (i) short-term feeder load forecasting, (ii) short-term substation transformer load forecasting and transformer rating, and (iii) next-year load pocket forecasting. The short-term feeder load forecasting allows a utility to reduce the possibility of feeder overloading. The substation transformer load forecasting and transformer rating application achieves similar goals at the distribution substation level. The load pocket forecasting software allows a utility to estimate load trends at different locations (called load pockets), to estimate next-year peaks, to calculate weather normalized factors, and to estimate the probability distribution of the next-year peak load. The use of these software applications significantly improved the efficiency and reliability of the distribution network.**

Keywords: load forecasting, feeder, transformer, load pocket, SmartGrid

I. INTRODUCTION

One of the important aspects of emerging Smart Grid technologies is measuring, transmitting, storing and processing electric power system data, such as voltage, current, phase angle, etc., and using this information for system control and management. In particular, operators of traditional distribution networks often do not have complete information about certain parts of the network such as three-phase measurements at substations and feeders, measurements along feeders, and so on. In many cases, certain SCADA data are monitored, but not stored.

This paper describes particular applications that demonstrate how measuring, storing and processing substation and feeder load measurements can help improve the distribution network efficiency and reliability. The monitored data have been used to develop transformer and feeder load models and apply these models to load forecasting in the distribution network. In particular, this paper describes three applications: (i) short term (from one hour up to seven days) feeder load forecasting, (ii) short-term substation transformer load forecasting and transformer rating, and (iii) next-year load pocket forecasting and Weather Normalization Factor (WNF) computations.

The goal of the first application, the short-term feeder load forecasting, is to provide the system operators with advanced warnings on potential normal feeder overloading. Once such overloading signal is received, the operators can take several measures to avoid the undesired event. These measures include load switching, feeder reconfiguration, load reductions, and voltage control. In future Smart Grid applications, load reductions can be implemented by time-differentiated pricing.

The second application combines load forecasting with transformer rating. Both load and temperature forecasts are used as inputs to the transformer rating software. Again, the transformer rating results can be used by operators for switching and load reduction decisions to protect transformers.

The third application deals with area planning. The goal is to compute Weather Normalization Factors for various areas served by a utility. The WNF is a ratio of the normal annual load to the observed annual peak load for a particular area (also called load pocket). Different load pockets may have different WNFs. This is typically for two reasons: (i) different weather conditions in different areas, and (ii) different load mixtures (industrial, commercial, residential; small houses, large houses, apartment buildings, and so on) in different areas. WNFs play an important role in area planning and capital budgeting.

Electric load forecasting is a useful tool needed and used by most electric utility companies to make some important decisions including decisions on purchasing and generation of electric power, load switching, and area planning. By the forecasting horizon load forecasting can be divided into three types: short-term (one hour up to a week), medium-term (a month up to three years), and long-term (over three years) [1].

In the literature majority of the works on load forecasting can be classified into four categories by the modeling and forecasting method used, namely statistical, intelligent systems, neural networks and fuzzy logic [2]. A more complete literature review was presented in [3, chapter 12].

In a Smart Grid environment, the importance of forecasting increases because of the growing complexity of challenges and the availability of more data inputs from a data-rich smart grid environment [4]. Additional data inputs include AMI loads, price information, and additional information from the grid.

The sequel of the paper is organized as follows. In Section II we provide a brief description of the model. In Section III we discuss the software for short-term feeder load forecasting. Section IV focuses on short-term substation transformer load forecasting and transformer rating. In Section V we introduce the next-year load pocket forecasting software. Discussions and conclusions are made in Section VI.

II. MODEL DESCRIPTION

The model, one version of which is described in [3], uses calendar information, weather information, and some additional information. We modified the model structure by adding an additive term. In mathematical terms the model is presented as

$$\begin{aligned} y_t &= F_t(d_t, h_t, w_t, p_t) \\ &= L_0(d_t, h_t) + L_1(d_t, h_t)\cdot f(w_t, p_t) + e_t, \end{aligned} \qquad (1)$$

where y_t is the actual load at time t;

L_0 is the weather-independent component;

L_1 is the normalized load, also independent of weather;

f is weather normalized factor;

d_t is the day of the week, 1, 2, …, 7;

h_t is the hour of the day, 0, 1, …, 23;

w_t are weather parameters including the temperature and humidity;

p_t are other factors including electricity prices, sunrise and sunset times;

e_t is a random error.

Similar to other statistical method, the model parameters are estimated using the historical data. The hourly weather information including ambient temperature and humidity measurements is provided by the NCDC (National Climatic Data Center). The hourly historical load data are extracted from the utility database. The applications need historical hourly load observations for at least one year.

To optimally estimate the parameters, we use the least square method and minimize the total squared residues, i.e.,

$$\min \Sigma_t[y_t - F_t(d_t, h_t, w_t, p_t)]^2. \qquad (2)$$

Problem (2) is an unconstrained nonlinear optimization problem. Due to the excessive number of parameters and the mixture of discrete and continuous parameters in the model traditional methods such as trust region method, Newton-Raphson method, quasi-Newton method, double dogleg method, conjugate gradient method, and Levenberg-Marquardt (LM) method are not very efficient. Instead we found a convenient form of the function F, as in (1) above, and developed a recursive algorithm that estimates the parameters.

We used Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and regression R^2 to measure the goodness-of-fit of the model. The definition of MAPE and MAD are

$$\text{MAPE}=\frac{1}{N}\sum_t \frac{|y_t - F_t|}{y_t}, \qquad (3)$$

$$\text{MAD}=\frac{1}{N}\sum_t |y_t - F_t|, \qquad (4)$$

where N is the number of observations used in the model.

The algorithm converges quickly, mostly in less than 10 steps. Figures 1-3 show the model Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and model R-squared at different iteration steps. Figure 4 shows the scatter plot between the model result and actual load for a load pocket.

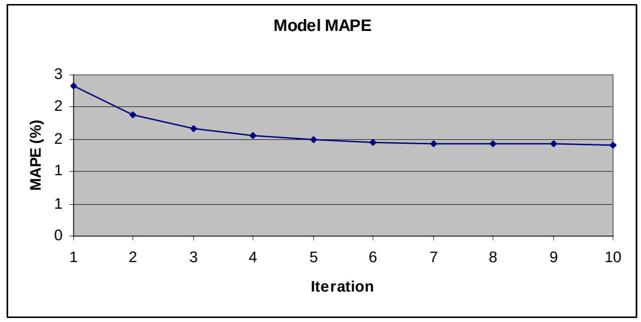

Figure 1. Model MAPE at different iteration steps

The model in (1) is relatively simple, robust and reliable. It can be easily used for different levels of forecasting: system level for an entire utility, substation/transformer level (load pocket), feeder level or even customer level load forecasting. It has been rigorously tested and used for years.

We remark that the installation of Advanced Meter Infrastructure (AMI) provides the possibility to use the AMI data to advance load models and improve load forecasts. We are currently investigating this approach.

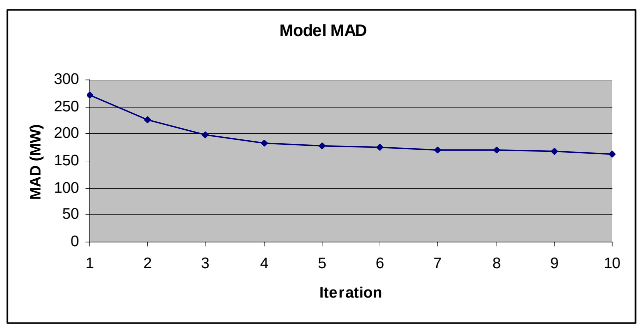

Figure 2. Model MAD at different iteration steps

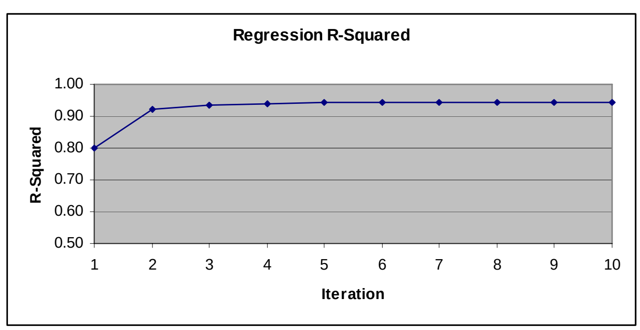

Figure 3. Regression R^2 at different iteration steps

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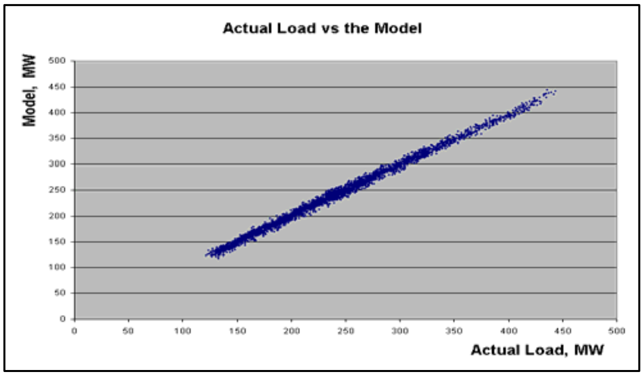


Figure 4. Scatter plot between model result and actual load

III. SHORT-TERM FEEDER LOAD FORECASTING

The goal of short-term feeder load forecasting is to provide the system operators with advanced warnings on potential normal feeder overloading. Once such an overloading warning is received, the operators can take several actions to avoid the overloading. These actions include load switching, feeder reconfiguration, load reductions, and voltage control. In future Smart Grid applications, load reductions can be implemented by time-differentiated pricing.

Our model can be easily adapted to provide feeder level load forecasting with a few additional procedures specially designed for feeder level load modeling and forecasting. These procedures include iterative filters during model training, periodic model updating, adaptive procedure and conservative adjustment.

The iterative filters are used to detect and exclude outliers in the training dataset. At each iteration step the Mean Absolute Percentage Error (MAPE) for the model is computed. The inclusion/exclusion criterion is to exclude all points with absolute percentage error greater than a certain threshold.

Periodic model updating is to use the most recent observations to replace the oldest observations in the original training dataset and build the model again on a periodic basis, say every two weeks.

Adaptive procedure uses the adaptive filtration technique to fit a simple linear regression between the actual load and the model result and then fine-tune the model result to reflect the most recent load pattern.

Conservative adjustment is implemented after the adaptive procedure by adding the underestimated amount at midnight (12AM) to the next day's forecasts. For example, if at midnight yesterday the actual load was 235 Amps but the forecast was 230 Amps, then 5 Amps will be added to the next day's forecasts. If the forecast was actually higher than the actual no adjustment is needed.

Another consideration in the implementation of feeder load forecasting is the heavy computation because sometimes there may be more than 1,000 feeders. The software was tested on actual feeders during summer peak times. It took at most 20 minutes to finish all calculations for about 140 feeders. The Mean Absolute Percentage Error (MAPE) was around 6%.

Figure 5 shows the actual and forecast loads (in Amps) for a feeder during June 1-July 9, 2010 in a Northeastern part of the USA.

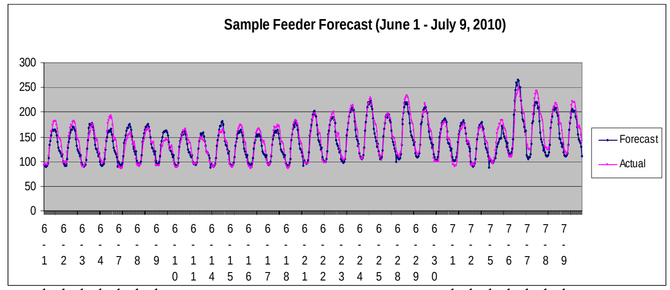


Figure 5. Actual and forecast loads for a sample feeder

IV. SHORT-TERM SUBSTATION TRANSFORMER LOAD FORECASTING AND TRANSFORMER RATING

Transformers are expensive assets to a utility. Overloading or overheating will generally reduce the useful life of a transformer. For this reason, it is important for a utility to make sure that their transformers are not overloaded or overheated. EPRI's PTLoad software can be used to determine a transformer's condition based on loading and temperature.

A developed application of short-term load forecasting to a transformer is shown in Figure 6. In the diagram load forecasts produced by load forecasting software are used as inputs to PTLOAD. PTLOAD calculates the transformer ratings and then the load forecasts as well as the transformer ratings are delivered to some internet based applications. For transformer level load forecasting, the accuracy of the one-day-ahead forecasts is around 4.5%.

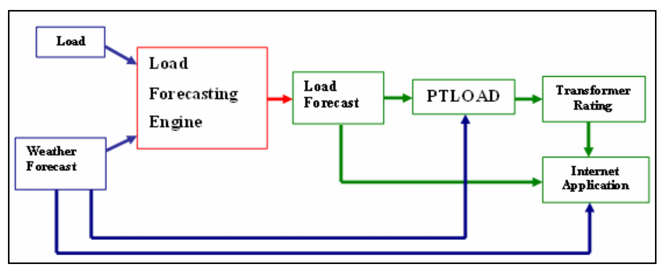


Figure 6. Application of short-term load forecasting

V. LOAD POCKET FORECASTING SOFTWARE

Load pockets refer to the aggregate of several close geographic areas [5]. It usually consists of a few substations or transformers. The concept provides flexibility in modeling regional loads. Our load pocket forecasting software makes the next year peak load forecasting.

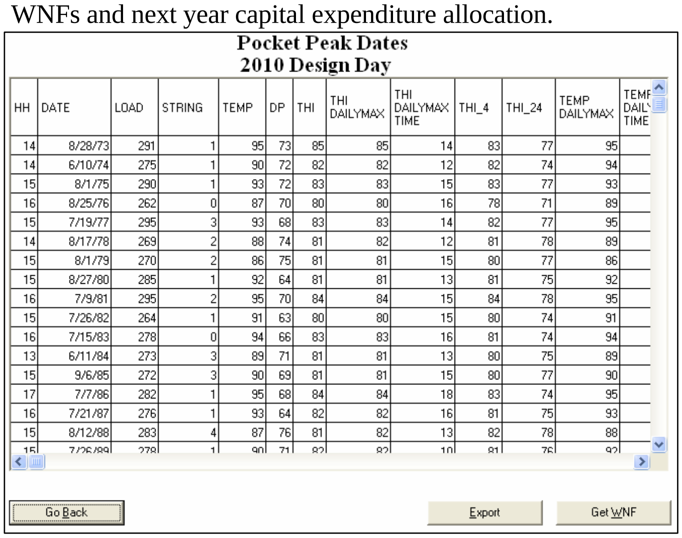
For each load pocket, the software computes the model described in (1). In addition to the model performance graphs shown in Figures 1-4, it also estimates the weather normalized loads. Based on the historical weather data and the current model, the software simulates the current load model on the historical weather data. A screenshot is shown in Figure 7. The user can select which of the past years to use to calculate the design-day parameters. The software analyzes and forecasts two types of peaks. The first type is the pocket peak, which is the maximal hourly load during the year. The second type is the system peak, which is the pocket load during the hour when the system experienced its peak.

One of the software inputs is the historical system peak dates and hours. Other inputs include historical hourly loads of distribution transformers and weather measurements, including temperature and humidity.

The software estimates historical peak days for load pockets (Figure 7). These are called pocket peak days and hours. The software then calculates the design-day parameters. For each load pocket, the design-day parameters are calculated for pocket peak days and for system peak days. Different load pockets may have different design days. An example of design-day parameters is presented in Tables II and III.

Once design-day parameters are calculated, the system calculates the ratio of the estimated load on the design day to the actual peak load. This ratio is known as the Weather Normalization Factor (WNF). The WNFs are useful in explaining what part of the annual load pocket peak is attributed to the specific weather conditions for that particular year. In addition, the software calculates weather-normalized trends as shown in Figures 8 and 9.

The software also contains a probability distribution calculator of the peak load for the next year (Figure 10). The user has two input parameters: the peak load value and the probability. The user can get the probability that the load will not exceed a particular value or get the value that the peak load will not exceed with a given probability. This peak distribution analysis is available for both pocket and system peak data. The software is used by area planners to compute WNFs and next year capital expenditure allocation.



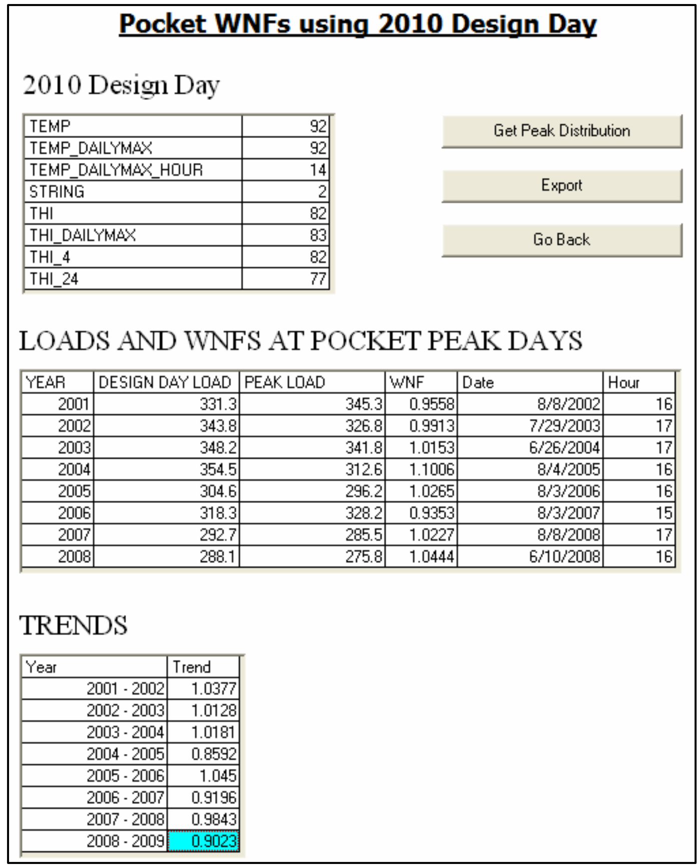
Pocket Peak Dates
2010 Design Day

HH	DATE	LOAD	STRING	TEMP	DP	THI	THI DAILYMAX	THI DAILYMAX TIME	THI_4	THI_24	TEMP DAILYMAX	TEMP DAILY TIME
14	8/28/73	291	1	95	73	85	85	14	83	77	95	
14	6/10/74	275	1	90	72	82	82	12	82	74	94	
15	8/1/75	290	1	93	72	83	83	15	83	77	93	
16	8/25/76	262	0	87	70	80	80	16	78	71	89	
15	7/19/77	295	3	93	68	83	83	14	82	77	95	
14	8/17/78	269	2	88	74	81	82	12	81	78	89	
15	8/1/79	270	2	86	75	81	81	15	80	77	86	
15	8/27/80	285	1	92	64	81	81	13	81	75	92	
16	7/9/81	295	2	95	70	84	84	15	84	78	95	
15	7/26/82	264	1	91	63	80	80	15	80	74	91	
16	7/15/83	278	0	94	66	83	83	16	81	74	94	
13	6/11/84	273	3	89	71	81	81	13	80	75	89	
15	9/6/85	272	3	90	69	81	81	15	80	77	90	
17	7/7/86	282	1	95	68	84	84	18	83	74	95	
16	7/21/87	276	1	93	64	82	82	16	81	75	93	
15	8/12/88	283	4	87	76	81	82	13	82	78	88	

Go Back Export Get WNF

Figure 7. Pocket Peak Dates (2010 Design Day)

Figure 7 shows pocket peak dates, the dates on which the pocket attained the maximal load during that year. Also shown are peak hours and weather parameters during those hours.



Pocket WNFs using 2010 Design Day

2010 Design Day

TEMP	92
TEMP_DAILYMAX	92
TEMP_DAILYMAX_HOUR	14
STRING	2
THI	82
THI_DAILYMAX	83
THI_4	82
THI_24	77

Get Peak Distribution
Export
Go Back

LOADS AND WNFS AT POCKET PEAK DAYS

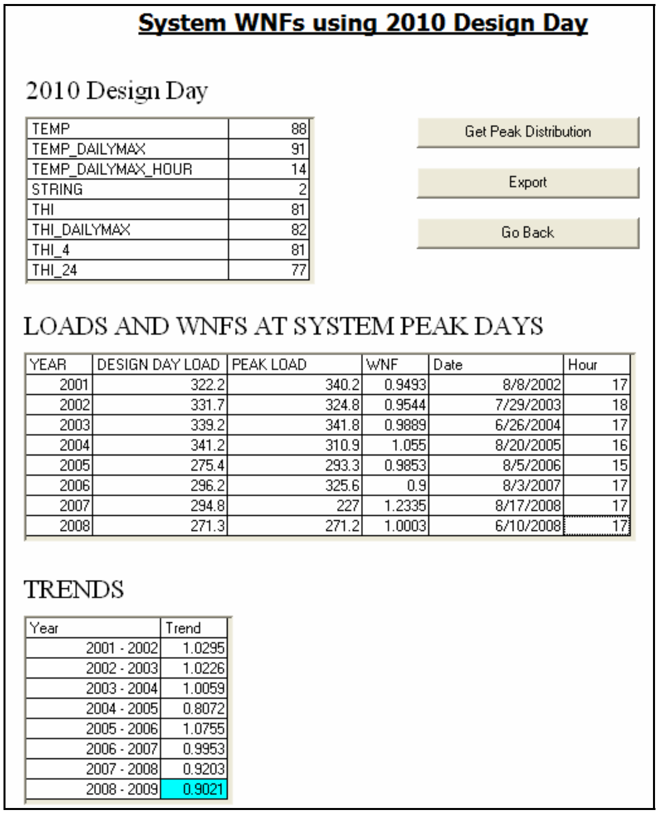
YEAR	DESIGN DAY LOAD	PEAK LOAD	WNF	Date	Hour
2001	331.3	345.3	0.9558	8/8/2002	16
2002	343.8	326.8	0.9913	7/29/2003	17
2003	348.2	341.8	1.0153	6/26/2004	17
2004	354.5	312.6	1.1006	8/4/2005	16
2005	304.6	296.2	1.0265	8/3/2006	16
2006	318.3	328.2	0.9353	8/3/2007	15
2007	292.7	285.5	1.0227	8/8/2008	17
2008	288.1	275.8	1.0444	6/10/2008	16

TRENDS

Year	Trend
2001 - 2002	1.0377
2002 - 2003	1.0128
2003 - 2004	1.0181
2004 - 2005	0.8592
2005 - 2006	1.045
2006 - 2007	0.9196
2007 - 2008	0.9843
2008 - 2009	0.9023

Figure 8. Normal Weather and Pocket WNFs

Figure 8 shows the WNFs calculated using the pocket peak dates and the year-to-year trends. A user may modify the last trend based on personal judgment.



TEMP	88
TEMP_DAILYMAX	91
TEMP_DAILYMAX_HOUR	14
STRING	2
THI	81
THI_DAILYMAX	82
THI_4	81
THI_24	77

YEAR	DESIGN DAY LOAD	PEAK LOAD	WNF	Date	Hour
2001	322.2	340.2	0.9493	8/8/2002	17
2002	331.7	324.8	0.9544	7/29/2003	18
2003	339.2	341.8	0.9889	6/26/2004	17
2004	341.2	310.9	1.055	8/20/2005	16
2005	275.4	293.3	0.9853	8/5/2006	15
2006	296.2	325.6	0.9	8/3/2007	17
2007	294.8	227	1.2335	8/17/2008	17
2008	271.3	271.2	1.0003	6/10/2008	17

Year	Trend
2001 - 2002	1.0295
2002 - 2003	1.0226
2003 - 2004	1.0059
2004 - 2005	0.8072
2005 - 2006	1.0755
2006 - 2007	0.9953
2007 - 2008	0.9203
2008 - 2009	0.9021

Figure 9. Normal Weather and System WNFs

Figure 9 is similar to Figure 8, but the WNFs are calculated using the system peak dates. Again, a user may modify the last trend.

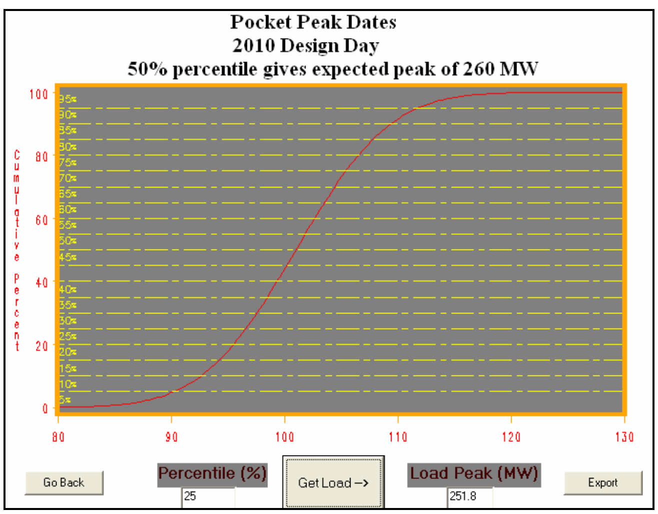


Figure 10. Peak Distribution Screenshot

Figure 10 shows the calculator for peak load distribution. A user can find the load value by entering the percentile (%), or find the percentile (%) by entering a load value. The 50th percentile corresponds to the expected peak.

VI. Discussions and Conclusions

This paper discusses three applications of distribution network load forecasting in the Smart Grid environment, where the SCADA data are stored, processed and the results of analysis are used to improve the system reliability and efficiency. The short-term feeder load forecasting enables operators to take appropriate measures in case of the potential overloading. These measures include load switching, feeder reconfiguration, load reduction and voltage control. The use of the application improves the reliability of the distribution network.

The substation transformer load forecasting and transformer rating application computes the transformer rating by combining load forecasts and temperatures and provides operators with warning of potential transformer overloading/overheating. The use of the application protects transformers from being overloaded or overheated.

The load pocket forecasting software allows a utility to estimate load trends at different load pockets, to estimate next-year peaks, to calculate weather normalized factors, and to estimate the probability distribution of next-year peak load. The use of this software improves the decision-making capabilities of area planning and capital budgeting and the reliability of service to the customers.

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