A Data-driven Dynamic Rating Forecast Method and Application for Long-term Power Transformer Planning

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Abstract—This paper presents a data-driven method for producing annual continuous dynamic rating of power transformers to serve the long-term planning purpose. Historically, research work on dynamic rating have been focused on real-time/near-future system operations. There has been a lack of research for long-term planning oriented applications. Currently, most utility companies still rely on static rating numbers when planning power transformers for the next few years. In response, this paper proposes a novel and comprehensive method to analyze the past 5-year temperature, loading and load composition data of existing power transformers in a planning region. Based on such data and the forecasted area load composition, a future power transformer’s loading profile can be constructed by using Gaussian Mixture Model. Then according to IEEE std. C57.91-2011, a power transformer thermal aging model can be established to incorporate future loading and temperature profiles. As a result, annual continuous dynamic rating profiles under different temperature scenarios can be determined. The profiles can reflect the long-term thermal overloading risk in a much more realistic and granular way, which can significantly improve the accuracy of power transformer planning. A real utility application example in Canada has been presented to demonstrate the practicability and usefulness of this method.

Index Terms—Dynamic Rating, Long-term System Planning, Gaussian Mixture Model, Transformer Thermal Aging

I. INTRODUCTION

A CCURATE long-term planning is the key to ensure balanced cost and reliability of power system in the next 5-10 years. As a critical and costly component, power transformer planning is an important part of long-term system planning process, in which the forecasted area load to be supplied by the transformer is compared with transformer’s rating to determine the proper transformer sizing.

However, most utility companies currently use static power transformer rating assumption, in many cases the nameplate ratings for long-term system planning [1-4]. These assumptions can be overly conservative or inaccurate as they do not reflect the dynamic temperature conditions in the planning region throughout a year. This is especially true for relatively cold areas such as Canada where the ambient temperatures are relatively low. According to IEEE std. C57.91-2011, the insulation deterioration of power transformers is a function of dynamic loading and ambient temperature. Proper combinations of dynamic loading and ambient temperature could safely allow transformer loading to exceed the nameplate rating without causing any damage. Therefore, to improve the cost-effectiveness of planning decisions, a scientific and realistic way to establish annual continuous dynamic rating for power transformers is required.

Previously, research works on dynamic rating mainly focused on real-time or near-future operations of system equipment [5-9]. Based on the monitoring of electrical and environmental conditions, real-time or near-future equipment ratings can be estimated or predicted and flexible loading operations or asset management decisions can be optimized accordingly to capitalize on such varying ratings. The research on establishing typical annual dynamic ratings to serve the long-term planning purpose has not been found. For such applications, there are two unique challenges:

1) No monitoring data is available for long-term future. Since the purpose of planning is to study the future load growth of an area, both long-term loading and temperature profiles are currently unknown and have to be estimated. Also, due to the high uncertainties over a long-term planning horizon, different scenarios may need to be studied.

2) Unlike operational dynamic rating which usually focuses on a short period of time such as a few hours or a few days, dynamic rating for long-term planning should be established on an annual basis to cover different seasons.

To tackle the above challenges, this paper proposes a novel and comprehensive data analytics method as shown in Fig.1. Each step in the flowchart is explained as follows:

- Step 1: the past 5-year hourly temperature data in the planning region is analyzed to establish three long-term annual temperature profiles under three scenarios;
- Step 2: for each future day in the 365-day profile, 5 historical days that have closest temperature and calendar characteristics are found;
- Step 3: within these 5 days, the relationships between the transformers’ load compositions and the future transformer’s forecasted load composition are analyzed by using Gaussian Mixture Model and Silhouette analysis in a probabilistic way;
- Step 4: By incorporating 24-hr loading profiles of existing transformers and the probabilistic relationships
established in Step 3, the future transformer’s normalized 24-hr loading profile can be constructed:

- Step 5: in the last step, the normalized 24-hr loading profile along with the forecasted 24-hr ambient temperature profile are fed into the transformer thermal aging model established according to IEEE std. C57.91-2011. The normalized profile is proportionally scaled up until accelerated transformer aging starts to appear. At this point, the power transformer’s dynamic rating for this particular profile day is determined since accelerated aging should be avoided for long-term power asset investment.

It is a basic fact that long-term hourly temperature profiles cannot be accurately forecasted [10]. However, given the past 5-year temperature data in a planning region such as a city or a town, the statistically representative long-term temperature profiles can be established. Three temperature scenarios high, medium and low are considered for planning purpose. In the high temperature scenario, for each day in the 365 days, the average daily temperatures in the past 5 years are compared and the day under the year with the highest average daily temperature is selected. For example, to create a profile for January 1st, January 1st’s in the past 5 years are compared by average daily temperature and it is found that 2016 January 1st has the highest daily temperature. Then the 24-hr temperature profile of 2016 January 1st is selected under the highest temperature scenario. This process continues until all 365 days’ profiles are selected from history and concatenated. Medium and low temperature scenarios use the same process except that when comparing among 5 years, instead of selecting the highest daily temperature day, the days with median and lowest daily temperatures are selected.

In addition to the above selection and concatenation process, a safety margin or global warming adjustment such as 1°C can be artificially added to all profiles. In this case, every hour under the three scenarios will be increased by 1°C.

The above method is unique in the sense that on the one hand, it reflects the future temperatures at three levels; on the other hand, it keeps the authentic temperature pattern within each day. Each profile day has a corresponding historical day in the past 5 years and hence has a high creditability.

B. Locating Similar Historical Days through Comparison

The next step is to find 5 similar historical days for each profile day established in subsection A. The purpose of this step is to find proper days based on which advanced data analytics can be further applied to construct the transformer’s loading profile, as to be discussed in Section III. To find similar days, two groups of features are considered: temperature and calendar features.

- Temperature features: as [11-15] suggest, temperature can significantly affect the loading behaviour. For example, air conditioning is more frequently used in hot days and the consumed power demand has a positive correlation with the ambient temperature. Ambient temperature may also affect customer behaviours since customers tend to stay indoor when it is very cold or hot outside and this behaviour often lead to increased power usage. To characterize daily temperatures, maximum, average and minimum temperatures in a day are chosen as features. For a 24-hr temperature profile, they are:

\[
T_a = \frac{\sum_{i=1}^{24} T_i}{24} \]

\[
T_h = \max(T_1, T_2, ..., T_{24}) \]

\[
T_l = \min(T_1, T_2, ..., T_{24})
\]

where \(T_1\) to \(T_{24}\) are the hourly temperatures in a day.

- Calendar features: as [14-15] suggest, workdays and holidays including weekends could have significantly different loading patterns. For example, in general,
residential customers consume more power on weekends and industrial customers consume more power on weekdays. Therefore, it is important to separate workdays and holidays into two groups and search for similar days within the two groups respectively.

Another introduced calendar feature is to reflect the position of a day in the annual cycle, i.e. day of the year. This feature could also imply different loading patterns. For example, although a major industrial load on two workdays in the Fall and Spring have similar temperatures, it has significantly different loading patterns at two very different times of a year. By using day of the year feature, the numerical difference on the yearly calendar can be reflected. According to [16], the day of the year feature can be mathematically defined as:

\[ Y = \sin \left( 2\pi \frac{D}{365} \right) \]  

(2)

where \( D \) is the day in 365 days. For example, \( D \) for January 1\textsuperscript{st} is 1 and \( D \) for December 31\textsuperscript{st} is 365. Sin function is used to reflect the cyclic characteristic and avoid one-way increase of the numerical value \( D \).

To locate 5 historical days with similar temperature and calendar features, at the beginning workdays and holidays are separated into two different groups due to significant distinctions between them. Then within each group, similar to many clustering analysis methods that rely on Euclidean distance to measure the differences between data points [17], this paper proposes to use the following Euclidean distance formula to measure the distances between a historical day \( D \) and the targeted profile day \( D' \).

\[ d = \sqrt{(T_a - T'_a)^2 + (T_h - T'_h)^2 + (T_l - T'_l)^2 + (Y - Y')^2} \]  

(3)

where \( T_a, T_h, T_l \) and \( Y \) are the temperature and day of the year features of the historical day \( D \); \( T'_a, T'_h, T'_l \) and \( Y' \) are the temperature and day of the year features of the profile day \( D' \). It should be noted that before applying (3), the features are all normalized to [0,1] by using (4) to eliminate magnitude and unit differences. The following equation can be used for normalization [17]:

\[ f_{\text{norm}} = \frac{f_{\text{raw}} - \text{Min}(f)}{\text{Max}(f) - \text{Min}(f)} \]  

(4)

where \( \text{Max}(f) \) is the maximum value observed in the feature \( f \) and \( \text{Min}(f) \) is the minimum value observed in feature \( f \); \( f_{\text{raw}} \) is the raw value of the temperature or calendar feature.

In the end, 5 historical similar days with minimum distances measured by (3) are selected out of the past 5 years and form the data windows for further analytics to be applied as discussed in the following sections.

III. FUTURE TRANSFORMER LOADING PROFILING

This section explains the details of Step 3 and 4 in the flowchart of Fig.1. The ultimate goal is to create the normalized 24-hr loading profile for the future transformer for a specific profile day in 365 days. An important concept called “Transformer Load Composition” is introduced and quantified. This is because the transformer total load is composed of residential, commercial and industrial loads supplied by the transformer. Different types of loads have different load shapes throughout a day and can respond to ambient temperatures in different ways.

In this section, an important probabilistic clustering method Gaussian Mixture Modelling and an efficient clustering quality evaluation method Silhouette analysis are explained. They are used together to quantify the probabilistic relationship between the future transformer and existing transformers based on transformer load composition. Based on the probabilistic clustering result, the 24-hr normalized loading profile for the future transformer can be constructed based on weighted average.

A. Transformer Load Composition

In general, most power transformers supply more than one type of loads. Approximately, the loads can be categorized into three types: residential, commercial and industrial loads. Transformer load composition can be described by the percentages of every load type. Residential load percentage \( R \), commercial load percentage \( C \) and industrial load percentage \( I \) should comply with:

\[ R + C + I = 1 \]  

(5)

When a customer load is connected or planned to be connected to a utility grid, it is a common practice for utility companies to assign the load to the above three categories with different electricity rates. Therefore, \( R, C \) and \( I \) can be easily determined. If needed, sub-categories of commercial and industrial loads can be determined on an individual load basis. However, this would require heavy manual classification work by human experts. In such a case, (5) becomes:

\[ R + \sum_{i=1}^{m} C_i + \sum_{j=1}^{n} I_j = 1 \]  

(6)

where there are \( m \) pre-determined commercial load subcategories and \( n \) pre-determined industrial load subcategories.

For a historical day, \( R \) can be calculated as:

\[ R = \sum_{i=1}^{m} \frac{L^R_i}{P_t} \times 100\% \]  

(7)

where \( P_t \) is the transformer peak loading in the day; \( m \) is the total number of residential loads supplied by the transformer; \( L^R_i \) is the loading of each residential load \( i \) at the transformer peaking time of the day. Similarly to residential load, transformer commercial load percentage is calculated as:

\[ C = \sum_{i=1}^{n} \frac{L^C_i}{P_t} \times 100\% \]  

(8)

where \( L^C_i \) is the loading of each commercial load \( i \) at the transformer peaking time of the day; \( n \) is the total number of commercial loads supplied by the transformer.

It should be noted for historical days, the loading values of existing customers in a day can be obtained from interval metering data and \( R \) and \( C \) can be calculated using (7) and (8); for a new area in a future day, \( R \) and \( C \) are estimated based on the expected numbers of residential, commercial and industrial customers along with their typical coincidental unit loading. When (5) is used to characterize transformer loading, only two percentage numbers out of the three are required to
characterize the load composition. This means the clustering dimensionality can be reduced to 2. For example, if \( R \) and \( C \) are selected, a power transformer can be characterized simply as a vector \((R, C)\); however when (6) is used, the transformer will need to be characterized with multiple dimensions and the clustering performance may be affected.

### B. Gaussian Mixture Modeling

Unlike deterministic clustering methods such as K-Means and Mean-shift which requires each data point to belong to a single cluster, Gaussian Mixture Model (GMM) is a powerful probabilistic clustering method [18-20]. When using GMM, a data point can belong to all clusters with certain membership probabilities. In statistics, a Gaussian mixture model is a mixture distribution that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with certain parameters to be determined. For clustering analysis, a Gaussian mixture function is comprised of several Gaussian components i.e. clusters, each identified by \( k \in \{1, \ldots, K\} \), where \( K \) is the expected number of clusters in the dataset \( U \). Each cluster \( k \) in the mixture has the following three parameters:

- **Mean** \( \mu_k \) which defines the centroid of cluster \( k \);
- **Covariance matrix** \( \Sigma \) of cluster \( k \).
- **Covariance matrix** \( \Sigma \) of cluster \( k \). In a \( n \)-dimensional case, cluster \( k \) can be written as a column vector:

\[
X = (X_1, X_2, \ldots, X_n)^T
\]

In the covariance matrix \( \Sigma \) shown below:

\[
\Sigma = \begin{bmatrix}
\text{Cov}_{1,1} & \cdots & \text{Cov}_{1,n} \\
\vdots & \ddots & \vdots \\
\text{Cov}_{n,1} & \cdots & \text{Cov}_{n,n}
\end{bmatrix}
\]  

each matrix element \( \text{Cov}_{i,j} \) is defined as:

\[
\text{Cov}_{i,j} = E[(X_i - E[X_i])(X_j - E[X_j])]
\]

where \( E \) is the expected value of its data array argument. In a one-dimensional case, \( \Sigma \) has only one element and it is equivalent to the variance of the data points in cluster \( k \).

The standard multivariate Gaussian probability density function is mathematically given as below:

\[
N(x|\mu, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma|^\frac{1}{2}} \exp\left(-\frac{1}{2}(x - \mu)^T \Sigma^{-1} (x - \mu)\right)
\]

Gaussian mixture model that consists of \( K \) Gaussian components is

\[
p(x) = \sum_{k=1}^{K} w_k \cdot N_k(x|\mu_k, \Sigma_k)
\]

where \( w_k \) is the weight of \( k \text{th} \) Gaussian component and it complies with:

\[
\sum_{k=1}^{K} w_k = 1, \quad 0 \leq w_k \leq 1
\]

For illustration purpose, a one-dimensional Gaussian mixture probability density function that consists of 3 Gaussian distributions \( x_1 \sim N(5,4) \),  \( x_2 \sim N(10,4) \) and  \( x_3 \sim N(15,4) \) with equal mixing weight \( 1/3 \) is plotted in Fig.2.

![Fig. 2. An example of one-dimensional Gaussian mixture probability density function](image)

The optimal mixture weights can be determined by using EM (Expectation-Maximization) algorithm for the maximization of likelihood of data points. Details of EM algorithm can be found in [21]. After mixture weights are determined, for a data point \( x \) in the dataset \( U \), it can simultaneously belong to all \( K \) clusters with the membership probability \( p_{sk} \) for each cluster:

\[
p_{sk} = \frac{w_k \cdot N_k(x|\mu_k, \Sigma_k)}{\sum_{k=1}^{K} w_k \cdot N_k(x|\mu_k, \Sigma_k)}, \quad x \in U
\]

where \( p_{sk} \) is the key parameter used to estimate future transformer’s normalized load profile and will be further used in subsection D.

### C. Clustering Quality Evaluation using Silhouette Analysis

Although GMM provides a mathematically sound way for probabilistic clustering analysis, the expected number of clusters \( K \) is unknown. One way to determine \( K \) is evaluating the clustering quality under different \( K \) values and selecting \( K \) which yields the best clustering quality. In order to evaluate clustering quality, Silhouette analysis is adopted [22]. In this analysis, an index called Silhouette coefficient \( Q_r \) is used to evaluate clustering quality. For a given data point \( r \in \text{cluster } S_r \), its \( Q_r \) can be mathematically calculated using the equations below:

\[
Q_r = \max \left\{ \frac{b_r - a_r}{\max(a_r, b_r)} \right\}
\]

\[
a_r = \frac{1}{|S_r| - 1} \sum_{s \in S_r, s \neq r} \left| d(r, s) - \frac{1}{|S_r| \sum_{v \in S_r} d(r, v)} \right|
\]

\[
b_r = \min \left\{ \frac{1}{|S_r| \sum_{v \in S_r} d(r, v)} \right\}
\]

where \( |S_r| \) is the number of members in cluster \( S_r \); \( S_v \) is any other cluster in the dataset; data point \( v \) is data point in \( S_v \); \( d \) is the Euclidean distance between two data points.

To evaluate the clustering quality, (16) calculates both the compactness and separation of produced clusters by GMM: \( a_r \) reflects the intra-cluster compactness. It is the average distance of data point \( r \) to all other points in the same cluster.
\( S_r \); \( b_r \) reflects the separation between other clusters and point \( r \). It is the smallest average distance of \( r \) to all points in every other cluster that does not contain \( r \) in the dataset; \( Q_r \) is the final index that combines \( a_r \) and \( b_r \). A good intra-cluster compactness and inter-cluster separation together will lead to a large \( Q_r \) value.

(16) is the calculation for a single data point \( r \). To evaluate the clustering quality of the entire dataset, average Silhouette coefficient is used and is given as below:

\[
Q_{avg} = \frac{1}{m} \sum_{i=1}^{m} Q_i
\]

where \( m \) is total number of data points in this dataset \( U \).

\( Q_{avg} \) for an initial range of \( K \) values is tested and then the \( K \) value resulting in the highest \( Q_{avg} \) is selected as the optimal \( K \) and used in GMM.

D. Constructing Normalized 24-hr Loading Profile for the Future Transformer

By using GMM, existing transformers within the 5 days identified in Section II along with the future transformer are clustered together based on their load composition features. An example of clustering result based on residential load percentage \( R \) and commercial load percentage \( C \) features for 80 transformers in 5 days with 6 clusters is shown in Fig. 3. \( R \) and \( C \) have been normalized by using (4).

\[
\text{Fig. 3. An example of transformer GMM clustering result}
\]

As previously discussed, (15) can be used to calculate the membership probability \( p_{xk} \) of the future transformer to each cluster. The future transformer’s normalized loading at \( t_{th} \) hour \( L_{pu}(t) \) can be calculated as below:

\[
L_{pu}(t) = \sum_{k=1}^{K} p_{xk} \cdot \frac{L_k(t)}{P_k}
\]

where \( L_k(t) \) is the loading of cluster centroid \( k \) at \( t_{th} \) hour; \( P_k \) is the peak loading of cluster centroid \( k \) in that day.

(18) is based on the principle that if the future transformer’s load composition on the profile day is similar to a group of existing transformers’ load compositions on similar historical days, its load shape (reflected as normalized profile) should also be similar to the load shape of such existing transformers. An example of constructed normalized 24-hr loading profile versus 6 cluster centroid normalized profiles is plotted in Fig. 4.

\[
\text{Fig. 4. An example of constructing normalized 24-hr loading profile}
\]

IV. POWER TRANSFORMER THERMAL AGING MODEL

This section explains the details of step 5 in the flowchart of Fig.1. IEEE std. C57.91-2011 explains the quantitative relationship between transformer thermal aging and influencing factors such as transformer loading and ambient temperature [22-23]. This section first explains the method to calculate equivalent aging factor and then explains the method to derive transformer dynamic load rating.

A. Calculate Equivalent Aging Factor

According to IEEE std. C57.91-2011, Fig. 5 summarizes the steps to calculate transformer equivalent aging factor: first, transformer top-oil temperature rise over ambient temperature is calculated; second, transformer hottest-spot temperature rise over top-oil temperature is calculated; third, the end of hour hottest-spot temperature is calculated; then the end of hour hottest-spot temperature is converted to transformer hourly aging acceleration factor; in the end, the transformer 24-hr equivalent aging factor is calculated.

\[
\text{Fig. 5. Flowchart of calculating transformer equivalent aging factor}
\]

In the first step, the transformer top-oil temperature rise over ambient temperature is calculated using equations below:
\[
\begin{align*}
\Delta \theta_{TO} &= (\Delta \theta_{TO,U} - \Delta \theta_{TO,I}) \left( 1 - e^{\frac{-24}{\tau_{TO}}} \right) + \Delta \theta_{TO,I} \\
\Delta \theta_{TO,U} &= \Delta \theta_{TO,R} \left[ \left( \frac{K^2 R + 1}{(R + 1)} \right)^n \right]
\end{align*}
\]  

(19)

where \( \Delta \theta_{TO} \) is the end of hour top-oil rise over ambient temperature in \(^\circ\)C; \( \Delta \theta_{TO,I} \) is the initial top-oil rise over ambient temperature in \(^\circ\)C; \( \Delta \theta_{TO,U} \) is the ultimate top-oil rise over ambient temperature in \(^\circ\)C; \( K \) is the ratio of current-hour loading to rated loading; \( \tau_{TO} \) is the transformer oil time constant for temperature differential between the ultimate top-oil rise and initial top-oil rise and can be provided by the transformer manufacturer; \( \Delta \theta_{TO,R} \) is a constant representing the top-oil rise over ambient temperature at rated loading on the tap position to be studied and can be provided by the transformer manufacturer; \( R \) is a constant representing the ratio of load loss at rated loading to no-load loss and can be provided by the transformer manufacturer; \( n \) is an empirical exponent. It is 0.8 for power transformers with natural convection flow of oil and natural convection flow of air over radiators (ONAN type). It is 0.9 for power transformers with natural convection flow of oil and forced convection flow of air over radiators by fans (ONAF type).

It should be noted that when applying (19), the initial top-oil rise over ambient temperature \( \Delta \theta_{TO,I} \) for each hour is unknown. A loop-based iterative calculation process is often used to solve this problem: \( \Delta \theta_{TO,I} \) in the first hour of the day is initialized to a low temperature number such as 0°C. Then \( \Delta \theta_{TO} \) in the first hour is calculated and also used as the input \( \Delta \theta_{TO,I} \) for the second hour. This process continues until values in all 24 hours get calculated. Then \( \Delta \theta_{TO} \) in the last hour is used as input \( \Delta \theta_{TO,I} \) for the first hour. The loop calculation continues until no hourly values get updated and this typically happens after a few iterations.

In the second step, the winding hottest-spot rise over top-oil temperature is calculated by using:

\[
\begin{align*}
\Delta \theta_{H} &= (\Delta \theta_{H,U} - \Delta \theta_{H,I}) \left( 1 - e^{\frac{-24}{\tau_{H}}} \right) + \Delta \theta_{H,I} \\
\Delta \theta_{H,I} &= \Delta \theta_{H,R} K^2 m \\
\Delta \theta_{H,U} &= \Delta \theta_{H,R} K^2 m
\end{align*}
\]  

(20)

where \( \Delta \theta_{H} \) is the end of hour winding hottest-spot rise over top-oil temperature in \(^\circ\)C; \( \Delta \theta_{H,I} \) is the initial winding hottest-spot rise over top-oil temperature in \(^\circ\)C; \( \Delta \theta_{H,U} \) is the ultimate winding hottest-spot rise over top-oil temperature in \(^\circ\)C; \( K \) is the ratio of last-hour loading to rated loading; \( \tau_{H} \) is the winding time constant at hot spot location and can be provided by the transformer manufacturer; \( \Delta \theta_{H,R} \) is a constant representing transformer hotspot differential and can be provided by the transformer manufacturer; \( m \) is an empirical factor. It is 0.8 for most power transformers and 1.0 for the ones that direct oil from the radiators or heat exchangers into the windings and force air over the radiators or heat exchanger by fans (ODAF type) [23].

In the third step, the end of hour hottest-spot temperature is calculated by using:

\[
\theta_{H} = \theta_{A} + \Delta \theta_{TO} + \Delta \theta_{H}
\]  

(21)

where \( \theta_{A} \) is the hourly ambient temperature in \(^\circ\)C.

In the fourth step, according to Arrhenius reaction rate theory, the hourly aging acceleration factor \( F_{AA} \) is calculated by using:

\[
F_{AA} = e^{\frac{15000}{583 - \theta_{H} + 273}}
\]  

(22)

In the fifth step, the transformer 24-hr equivalent aging factor \( F_{EQA} \) is calculated by using:

\[
F_{EQA} = \frac{\sum_{t=1}^{24} F_{AA,t}}{24}
\]  

(23)

where \( t \) is the hour in a day.

**B. Determine Transformer Daily Dynamic Rating**

From the long-term planning perspective, it is desired that the 24-hr equivalent aging factor \( F_{EQA} \) is 1.0. This is because when \( F_{EQA} \) is less than 1.0, the power transformer is underutilized against its normal insulation life (underloading situation); when \( F_{EQA} \) is greater than 1.0, the power transformer is overutilized against its normal insulation life and the overall life will be shortened (overloading situation). Therefore, keeping \( F_{EQA} \) as one is used as the criterion to determine the daily transformer load rating.

In Section III, the normalized 24-hr loading profile has been constructed based on load composition. Since it is normalized, it only captures the load shape and does not reflect the actual magnitude. In this step, the normalized profile is proportionally scaled up with a small step change and at each step, the corresponding \( F_{EQA} \) gets calculated until \( F_{EQA} = 1 \) is reached. An example of a 50MVA power transformer’s 24-hr thermal aging simulation during a day is shown in Fig.6. In this example, \( F_{EQA} = 1 \) and as can be seen, a significant portion of the transformer load \( K \) is greater than rated loading 1.0 p.u. The maximum transformer load during the day is actually 1.55 p.u. This means the transformer dynamic rating for the day is 77.5MVA, for the particular load composition and temperature profile in this example.

**V. APPLICATION EXAMPLE**

The proposed method has been applied to a major utility company in West Canada for one of its planning regions City of Calgary in the Alberta Province. Data from 2013 to 2018 were used for analysis. The results are presented and discussed in detail in this section.

**A. Results of Annual Temperature Profiles**
By using the method discussed in Section II, three long-term annual temperature profiles for City of Calgary are established as shown in Fig.7. The historical weather data was obtained from [25].

**B. Results of Annual Dynamic Rating Profiles**

By using the method discussed in Section III and IV, three annual dynamic rating profiles in 2023 with an assumed future load composition (60%, 30%) for a 50MVA ONAF power transformer typically used by the utility is given in Fig.8. In general, the summer months (May to Sep.) have lower rating than winter months (Oct. to Apr.) and this is because summer has higher ambient temperatures. Also, the high temperature scenario yields low dynamic rating and vice versa.

**C. Sensitivity Analysis**

Sensitivity analysis was also applied to analyze transformer ratings for different area load compositions. 4 area load types-residential heavy, commercial heavy, industrial heavy and balanced were considered. Load compositions for each load type in the planning area in 2023 were assumed and listed in Table I. A typically used 50MVA ONAF power transformer is considered. It is discovered that residential heavy and commercial heavy load types have relatively higher ratings while industrial heavy and balanced load types have lower ratings. This is because the industrial loads in Calgary do not fluctuate dramatically as residential and commercial loads in a day and often operate constantly at a high level. This kind of load behavior affects the cooling of transformer temperature.

**TABLE I: SENSITIVITY ANALYSIS**

| Area Load Type    | Area Load Composition (R,C) | Temperature Scenario | Summer Average Rating (MVA) | Winter Average Rating (MVA) |
|-------------------|------------------------------|----------------------|-----------------------------|-----------------------------|
| Residential Heavy | (80%,10%)                    | High                 | 68                          | 78                          |
| Commercial Heavy  | (10%,80%)                    | High                 | 67                          | 72                          |
| Industrial Heavy  | (10%,10%)                    | High                 | 64                          | 68                          |
| Balanced          | (33.3%,33.3%)                | High                 | 65                          | 71                          |
| Residential Heavy | (80%,10%)                    | Medium               | 71                          | 81                          |
| Commercial Heavy  | (10%,80%)                    | Medium               | 70                          | 76                          |
| Industrial Heavy  | (10%,10%)                    | Medium               | 66                          | 71                          |
| Balanced          | (33.3%,33.3%)                | Medium               | 67                          | 74                          |
| Residential Heavy | (80%,10%)                    | Low                  | 72                          | 85                          |
| Commercial Heavy  | (10%,80%)                    | Low                  | 72                          | 79                          |
| Industrial Heavy  | (10%,10%)                    | Low                  | 67                          | 75                          |
| Balanced          | (33.3%,33.3%)                | Low                  | 68                          | 78                          |

**D. Implications for Long-term Transformer Planning**

The above results showed great value of the proposed method for utility long-term planning. At the beginning, planning engineers only need to forecast the load compositions of the planning area to be supplied by the future transformer. Different load composition scenarios/ranges can
be considered if needed. Then the annual dynamic ratings of the transformer can be produced using the proposed method. On the other hand, planning engineers will also forecast the loading growth in different years over the planning horizon (sometimes split to summer and winter seasons). The forecasted loading can be compared with the forecasted power transformer dynamic rating to determine the proper sizing of a new transformer or the need to upgrade an existing transformer to a larger size and the timing of such installation or upgrade. In this process, as per the utility company’s planning practice and risk tolerance level, planning engineers can also assume proper temperature adjustment, select a temperature scenario out of the three or produce results under all three scenarios for sensitivity analysis.

VI. CONCLUSIONS

This paper addresses an important problem in utility companies that has not been researched before – how to produce annual continuous dynamic rating of power transformer for long-term planning purpose. To respond to this need, this paper proposes a novel and comprehensive data analytics method to process the past 5-year temperature, loading and load composition data of existing power companies that has not been researched all three scenarios for sensitivity analysis.

Among other things, the outcomes of the proposed method include:

• Three long-term annual temperature profiles for the planning region can be established;
• For any day in a year, a future power transformer’s loading profile can be constructed using Gaussian Mixture Model and Silhouette analysis;
• A power transformer thermal aging model can be established with respect to IEEE std. C57.91-2011. Future loading and temperature profiles under different scenarios can be incorporated into such model and the corresponding aging effect can be quantified;
• Three annual continuous dynamic rating profiles of the future transformer can be determined under three long-term temperature scenarios.

This paper also presents the details of an application example for a utility company in West Canada and explained how such results can help utility planning engineers with power transformer planning. It demonstrates great practical value and feasibility of the proposed method in real world.

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