Using fuzzy binary relations to characterize total power-load curve

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Abstract. The paper proposes an approach to load forecasting on the shop floor level of power distribution, as well as to forecasting the loads of process-sharing subdivisions for the dispatching of industrial power supply. The approach implies mathematical representation of process linkages inside a production facility as fuzzy relations. Fuzzy relations are described quantitatively by the incidence matrices, which are decomposed on multiple levels depending on the desired accuracy. It is proposed to find the coordinates of an ordered resulting curve, from which a daily curve can be derived on the known-form basis. The approach can be used by the parameter and production teams of the Chief Power Engineer's office of an industrial enterprise to make day-ahead curves as well as standard long-term daily curve.

Keywords: power system, dispatching, electrical load forecasting, resulting curve, individual curve, process sharing, fuzzy binary relations, incidence matrix, binary relation decomposition, α-level.

1. Introduction

Electrical load forecasting is fundamental to dispatching in both short-term (day-ahead) planning and mid- or long-term planning (making standard seasonal daily curves). When dispatching the power supply system of a large industrial enterprise using in-house generation, load forecasts are necessary for handling grid and power-plant equipment repair jobs, for designing voltage control measures, for trading in the wholesale electricity market, for drafting the generation programs for in-house power plants, as well as for some other applications. Of practical interest are the 110- to 220-kV load curves of tie stations and the 3- to 10-kV load curves of main stepdown substations, i.e. the loads of shops and shops subdivisions. Examples in steelworks include blast furnaces, arc furnaces, or converters used in blast-furnace, arc-melting, and BOF shops; large-, medium-, and small-section mills in section rolling shops; plate and skin rolling mills in cold plate rolling shops, etc.

Load forecasting has been the subject of numerous papers in both process and commercial dispatching. Using time series to account for weather factors in one way or another is one of the most common approaches to load forecasting. In this approach, industrial loads are deemed constant and belong to the curve baseline. Thus, paper [1] considers the method of seasonal curves to make hourly forecasts on the basis of retrospective data. A seasonal modification of the Holt-Winters method, which is a smoothing method, is applied in [2] to the Middle-Eastern weather, where summer loads exceed winter loads. The authors use this method to forecast peak loads in the short term. Weather uncertainty in day- to week-ahead forecasting is considered in [3]. Paper [4] models the load curve by a hybrid time series with two components: a linear autoregressive model (moving average) and a non-linear support vector regression model. Forecasting is based on CSA, which is an evolutionary algorithm.

Paper [5] considers a two-staged approach to forecasting: the first stage is to project mean load for a day ahead, while the second stage is to project loads on an hourly basis. This approach uses least squares of support vectors. The model is trained on daily data spanning three years. The authors recommend this approach for use in deregulated electricity markets [23-25].
Artificial neural networks are fairly widespread, too. Paper [6] considers a hybrid ANN training algorithm based on a modified harmony search method, which searches for solutions in multiple directions. The authors make emphasis on short-term forecasting in commercial dispatching. Time series is represented by an autoregressive model (moving average). For long-term (two to five years) forecasting, paper [7] proposes an hierarchical neural network with time windows, which consists of two self-assembled layers and a single-layer perceptron. Paper [8] proposes combining ANNs with fuzzy logic based on the Levenberg–Marquardt training algorithm. The authors adopt the Gaussian membership function, the Takagi–Sugeno fuzzy inference rule. Paper [9] dwells upon the efficiency of using ANNs for forecasting in SCADA systems. Using fuzzy numbers in forecasting is the subject of paper [10], which proposes using regression equations with fuzzy coefficients to account for weather effects on the peak loads. Electrical load forecasting is considered mandatory for SmartGrids. The paper [11] dwells upon forecasting peak loads by means of ANNs; however, the facility researched there is a large non-industrial building, where one could simply arrange data collection from all power points. Load curve modeling to forecast losses in distribution grids is usually considered a separate challenge. Paper [12] proposes using exponential dependencies to approximate ordered load duration curves, then use those to find the load shape coefficients to be used in loss calculations. Paper [13,14] proposes representing curves as fuzzy intervals. Automatic frequency control in power systems has specific requirements to load forecasting methods. Paper [15] considers a Kalman filter-based approach to load forecasting, which also uses evolutionary algorithms to optimize load distribution between power units. In this case, predictive accuracy is tested by the frequency fluctuation amplitude as observed during regulation. Some papers dwell upon finding the probabilistic properties of electrical loads. Paper [16] presents the results of testing residential loads against various distribution laws. The authors conclude that gamma distribution and log-normal distribution most accurately describe this load scenario. Paper [17] describes an active experiment carried out in a British residential area; the experiment consisted in switching off district heating and hot water supply to record how using electrical appliances to the same end would affect electrical loads and their probabilistic properties [26]. User classification may also be based on load curves and use different approaches. For instance, paper [18] dwells upon classifying Regny daily curve classification based on entropy-enabled clustering. The proposed approach focuses on identifying various user groups in retail electricity markets to improve tariffs; it can also be used to manage the demand. Paper [19] uses symbolic approximation for smart metering-based clustering. Paper [20] uses mixed time-series models to the same end. Literature review shows that most researchers propose approaches focused on power system management, electricity market infrastructure functioning, and the operation of urban, rural, and sundry non-industrial distribution grids. Industrial load forecasting requires taking into account the specifics of the enterprise-wide and facility-specific processes [27].

2. Binary Relations for Process Sharing

When forecasting electrical loads in industrial shops, one often has to find such resulting curve characteristics as maxima, minima, and means on the basis of similar characteristics of main-unit load curves. It is thereby necessary to consider the inter-related nature of such units, which is due to their shared processes. Paper [21] describes a method for taking into account such interrelation; it is based on matching electrical loads to a normal distribution and can be used to find the mathematical expectation and the variance of the resulting curve values. However, analyzing the load curves at 3 to 10 kV (shop-level distribution substations) to 110 kV (main stepdown substations) in a large steelworks setting reveals that normal distribution is rarely seen. This first of all applies to hot and cold rolling facilities. In this case, using the Pearson pairwise correlation coefficient as proposed in [21] is not an option; describing the load by two values (mathematical expectation and variance) is inappropriate; and using nonparametric estimates such as the Spearman coefficient or the Kendall coefficient does not enable one to derive the load from the known correlation coefficient; this is why this paper proposes an approach based on fuzzy sets. When using this approach, load curves must be converted from actual values into linguistic variables, where scoring is the most convenient option, e.g. 1 to 10. Scoring can be done as follows:
where $B_{\text{max}}$ is the maximum points; $P_{i,\text{inst}}$ is the installed capacity of the receivers generating the $i$th load curve; $P_{ik}$ is the $i$th curve capacity on the $k$th stage, actual value; $P_{i(b)}$ is the score for the same. For the resulting (shop-wide) load curve, adopt the values $P_{\Sigma_{\text{inst}}}$, $P_{\Sigma_k}$, and $P_{\Sigma(b)}$, respectively.

The correlation between the fuzzy sets of any electrical loads $P_1$ and $P_2$ can then be represented by the fuzzy relation \( \Gamma = P_1 \times P_2 \), the quantitative characteristics of which (the membership function values) are written as the incidence matrix $J_\Gamma$. These values can be found by an expert, e.g. by pairwise comparisons.

Let the incidence matrix of a binary relation between the single-unit load $P_i$ and the shop-total load $P_\Sigma$ be as follows (2):

\[
P_i \begin{bmatrix}
0 & 0 & 0.1 & 0.5 & 0 & 0 & 0.9 & 0.8 & 0 & 0 \\
0 & 0 & 0.3 & 0.7 & 0.1 & 0 & 0 & 0 & 0 & 0 \\
0.4 & 0.5 & 0.1 & 0 & 0 & 0.1 & 0 & 0 & 0 & 0 \\
0.8 & 0.7 & 0.2 & 0 & 0 & 0 & 0.5 & 0.4 & 0 & 0.1 \\
0 & 0 & 0 & 0 & 0.4 & 0.7 & 0.2 & 0 & 0 & 0 \\
0 & 0.1 & 0.1 & 0 & 0 & 0 & 0.8 & 0.9 & 0.8 \\
0 & 0 & 0.2 & 0.4 & 0.5 & 0.4 & 0.1 & 0.1 & 0.1 & 0 \\
0.5 & 0.5 & 0.5 & 0 & 0 & 0.3 & 0.1 & 0 & 0 \\
0.1 & 0.3 & 0 & 0 & 0.5 & 0.6 & 0.7 & 0.8 & 0 & 0.1 \\
0 & 0 & 0 & 0.7 & 0.7 & 0 & 0 & 0 & 0 & 0
\end{bmatrix} P_\Sigma = J_\Gamma \begin{bmatrix}
1 \\
2 \\
3 \\
4 \\
5 \\
6 \\
7 \\
8 \\
9 \\
10
\end{bmatrix} \tag{2}
\]

In (2), the columns of the matrix $J_\Gamma$ correspond to the $P_i$ scores, while the rows correspond to the $P_\Sigma$ scores.

To find the resulting load curve maximum, apply the Bayesian test; use the expert-determined membership function values as the score weights. For each matrix row $J_{P_i \times P_\Sigma}$, find the following value:

\[
M_{i,\alpha} = \frac{\sum_{j=1}^{\text{max}} j \mu_{ij,\alpha}}{\sum_{j=1}^{\text{max}} \mu_{ij,\alpha}} \tag{3}
\]

Here $B_{\text{max}}=10$ is the maximum score, $\mu_{ij,\alpha}$ is the membership function value provided that it satisfies some chosen level $\alpha$.

Having decomposed the fuzzy relation $\Gamma$ on level $\alpha$, e.g. for $\alpha \geq 0.8$, for the first row of $J_{\Gamma_{\alpha}}$ obtain:

\[
M_{1,\alpha} = \frac{0.9 \cdot 7 + 0.8 \cdot 8}{0.9 + 0.8} \approx 7.5
\]

Find the mean of the obtained sequence. For example, at $\alpha \geq 0.8$ the sequence $\{7.5; 0; 0; 1; 0; 9; 0; 0; 8; 0\}$, the mean is 7. Following the adopted scoring system, the value can be converted into an actual value. To estimate the ordered resulting load curve, assume multiple $\alpha$ values, e.g. 0.8 to 0.1 with a pitch of 0.1, then follow the algorithm above. The number of $\alpha$-levels in use depends on the desired accuracy. This produces the following matrix:
Computing the mean and rounding produces:

\[
\begin{bmatrix}
7.5 & 0 & 0 & 1 & 0 & 9 & 0 & 0 & 8 & 0 \\
0 & 4 & 0 & 2 & 6 & 0 & 0 & 0 & 7 & 4.5 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 6 & 0 \\
4 & 0 & 2 & 7 & 0 & 0 & 5 & 2 & 5 & 0 \\
0 & 0 & 1 & 8 & 5 & 0 & 5 & 0 & 0 & 0 \\
0 & 3 & 0 & 0 & 0 & 0 & 0 & 7 & 2 & 0 \\
0 & 0 & 0 & 3 & 7 & 0 & 3 & 0 & 0 & 0 \\
3 & 5 & 5 & 10 & 0 & 2.5 & 8 & 8 & 5.5 & 0
\end{bmatrix}
\begin{align*}
\alpha &\geq 0.8 \\
\alpha &\in [0.7;0.8] \\
\alpha &\in [0.6;0.7] \\
\alpha &\in [0.5;0.6] \\
\alpha &\in [0.4;0.5] \\
\alpha &\in [0.3;0.4] \\
\alpha &\in [0.2;0.3] \\
\alpha &< 0.2
\end{align*}
\]  

(4)

The ordered sequence will be \{7; 6; 6; 5; 5; 4\}. This means that the value 4 of the resulting curve corresponds to the values \[0;2.5\] of the individual curve; the value 5 corresponds to \[2.5;6,25\]; 6 to \[6,25;8,75\]; and 7 to \[8,75;10\]. Figure 1 shows the resulting scale.

**Figure 1.** Y-value correlation of the singular and resulting curves for the calculation example cited

Given what is shown in Figure 1, the resulting ordered curve for the total of running in-shop units (scored) will be as follows, see Figure 2. For example, assume that the ordered individual unit load curve follows the sequence \(P_{ib}=[10; 9; 7; 6; 5; 4; 4; 2; 1]\). The dashed line shows the unit-specific load curve, while the solid line shows the resulting shop-wide curve. Figure 2 can be used to derive the coordinates of the ordered shop-wide load curve from the coordinates of the ordered unit-specific curve. In order to stage the curve by hours, one has to convert this histogram on the basis of the subdivision-specific curve shape data.
To identify the interrelations between the loads of connections powering the process-sharing shop facilities (e.g., $P_i$ and $P_j$), this paper proposes using the composition of binary relations $\Gamma_{\Xi}=P_\Xi \times P_\Xi$ and $\Gamma_{\Sigma}=P_\Sigma \times P_\Sigma$.

Binary relations between load curves can be classified as symmetric similarity relations, i.e. $P_j \times P_\Xi = P_\Xi \times P_j$. Therefore, for the relation $\Gamma_{ij} = \Gamma_{\Xi} \circ \Gamma_{\Sigma}$, the incidence matrix $J_{\Gamma_{ij}}$ can be derived as the max-min multiplication of the matrices $J_{\Gamma_{\Xi}}$ and $J_{\Gamma_{\Sigma}}$.

Let the matrix $J_{\Gamma_{\Xi}}$ be as follows:

$$
J_{\Gamma_{\Xi}} = 
\begin{bmatrix}
0 & 0 & 0 & 0 & 0.3 & 0.8 & 0.3 & 0 & 0 & 0 \\
0.4 & 0.1 & 0.7 & 0 & 0.2 & 0.1 & 0 & 0 & 0 & 0 \\
0 & 0.5 & 0 & 0.6 & 0.9 & 0.3 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

Then the desired matrix $J_{\Gamma_{ij}}$:

$$
J_{\Gamma_{ij}} = 
\begin{bmatrix}
0 & 0 & 0 & 0 & 0.3 & 0.4 & 0.5 & 0.6 & 0.7 & 0.6 & 0.5 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

(6)
This matrix can be used similarly to (2) to obtain the respective scale.

Actual Y-values of the load curve of interest can be found by the formula inverse to (1):

\[ P_{ik} = P_{icyc} \left(1 - \frac{P_{ik(c)}}{B_{\text{max}}}ight) \]  

(8)

3. Conclusions

The paper proposes a method for generating resulting load forecasts for a production facility or another structural subdivisions on the basis of the pre-existing machine-specific load curves. The approach is based on using a fuzzy binary relation incidence matrices further decomposed on multiple levels depending on the desired accuracy; it takes into account the time divergence of receiver operations and the uncertainty of their respective loads, as well as the fact that the load, being a random variable, does not match normal distribution. The proposed approach focuses on planning the operation of power supply systems running within large industrial companies, as well as on cooperation with power suppliers.

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