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# Optimization of low voltage distribution network configuration using forecasts based on Advanced Metering Infrastructure data

***Streszczenie.*** *W artykule przedstawiono praktyczne podejście do optymalizacji konfiguracji rzeczywistej sieci rozdzielczej nn. Opisano zbiór danych wejściowych, metody optymalizacji i uzyskane wyniki. Na podstawie prognoz obciążenia w poszczególnych węzłach odbiorczych określono optymalne konfiguracje. Prognozy wykonano czterema metodami prognostycznymi. Optymalizację konfiguracji sieci przeprowadzono za pomocą dwóch opracowanych metod: heurystycznej i genetycznej. Na podstawie przeprowadzonych symulacji sformułowano praktyczne wnioski.* ***(Optymalizacja konfiguracji sieci rozdzielczej niskiego napięcia z wykorzystaniem prognoz opartych na danych AMI)***

***Abstract***. *The article presents a practical approach to optimizing the configuration of a real LV distribution network. The set of input data, optimization methods and obtained results are described. The optimal configurations were determined on the basis of load forecasts in individual load nodes. Forecasts were made using four forecasting methods. Optimization of the network configuration was carried out using two developed methods: heuristic and genetic. Based on the simulations, practical conclusions were formulated.*

**Słowa kluczowe**: elektroenergetyczne sieci rozdzielcze, optymalizacja konfiguracji sieci, prognozowanie zapotrzebowania, system informatyczny.
**Keywords**: power distribution networks, optimization of network configuration, demand forecasting, IT system.

## Introduction

Business and technical processes – especially in commercial activities – are strongly connected with losses that cannot be avoided. Costs associated with the transmission of electricity can reach up to 40% of the total energy price for households. The power distribution network is the most expensive component of the power system considering the volume of electrical energy losses. Reducing losses in the electricity distribution process is becoming more and more important and is also required by legal regulations. Optimization of the network configuration is one of the basic non-investment activities leading to reduction of power losses in the distribution network. Introduction of optimization methods can lead to a reduction in total power losses even by several percent. Distribution networks are built as meshed networks (although with a large share of radial subnetworks non connected in loops) and work in open configuration, which is the most suitable for protecting and coordinating connection schemes in an unidirectional power flow. To optimize network configuration is to specify the operational structure of the type tree minimizing energy loss in normal working conditions. Other functions, such as reducing overloads or improving the voltage profiles of power lines, can also be considered appropriate, but usually minimizing energy loss also gives optimal results in respect to other criteria.

There are many works concerning optimization of the network configuration. Usually methods base on deterministic loads (e.g. past measurements, arbitrary values). In this paper a more practical approach is presented. In the real world, we are looking for an optimal network configuration in the future. So that network can be prepared to upcoming events. Proposed approach (configuration optimization) uses forecasted load values determined utilizing AMI measurements.

In this paper, firstly the mathematical model of distribution network reconfiguration is given. Then the electrical power demand forecasting method was chosen, taking into account naive method, method based on energy consumers profiles, ANN, multilayer perceptron and XGBoost. Finally, two algorithms for distribution network reconfiguration are compared:

1. Heuristic (based on power flow algorithm).
2. Genetic algorithm.

Optimization calculations are performed using forecasted demand value. Network configurations determined in the calculations were verified by power flow analysis using real network nodes power demands taken form automated metering systems. The advantages and disadvantages of various algorithms are analysed.

In the presented article, the ELGrid2020 system supporting the development and optimization of the operation of distribution power grids, developed by Globema in cooperation with the Institute of Power Engineering of the Warsaw University of Technology, was used to perform optimization calculations. The system enables, among others: estimating loads in the MV/LV distribution network, power flow calculation, network configuration and voltage levels optimization.

In practical applications in solving the network configuration optimization task, heuristic and metaheuristic algorithms play a dominant role. The heuristic power flow algorithm [1] can qualify to the group of "greedy" algorithms, however, it is very simple and quick to use. In branch exchange algorithms are merged into the optimized network of one of the disabled in the state normal of the branch, resulting in a loop. In such a loop, one of the branches to be shut down is searched for. Examples of branch exchange algorithms are presented in [2, 3]. Following algorithms are also used to solve the problem: simulated annealing [4, 33], genetic algorithms [5, 27, 34], harmonic search [6], swarm algorithms [28] and others [7, 8, 9, 10, 36]. In the papers [33, 35, 36] different methods of optimization of MV network structures are presented. The test case consists of 114 loads with identical power demand. In [35] the utilization of evolutionary algorithms and neural networks are presented, and in [33] the use of an ecosystem algorithm is presented. The author showed that the ecosystem method in most cases achieved better solutions and better work stability compared to evolutionary algorithms and particle swarm optimization algorithms, although the ecosystem algorithm is relatively slow converging. In the paper [11] a customized evolutionary algorithm FPEO has been introduced and applied to power distribution network reconfiguration. The recombination operators of the algorithm are designed to preserve feasibility of solutions (radial structure of the network) thus considerably reducing the size of the search space. In particular, the computational cost of the optimization process is much lower than for most of competitive approaches. The two-stage robust optimization model for the distribution network reconfiguration problem is proposed in the paper [12]. The authors defined first-stage decision as to configure the radial distribution network; the second-stage decision as to find the optimal AC power flow of the reconfigured network for given demand realization. The column-and-constraint generation algorithm [13] was used to solve the proposed two-stage robust problem. Paper [29] presented Firefly Algorithm (FA) - a swarm metaheuristic based on firefly behaviour. In the paper [14] a method based on the Cuckoo Search Algorithm is proposed. The algorithm is inspired by the strategic reproduction of cuckoos.

In the short-term electrical power demand forecasting, Support Vector Machines, Particle Swarms, artificial intelligence including Artificial Neural Networks and many others, have been used for years. Paper [15] described a clustering-based bootstrapping method to increase the accuracy of multistep ahead point forecasts. Method proposed in this paper called SSA.KM.N, combines singular spectrum analysis and K-means clustering-based generation of Gaussian normal distribution to generate electricity load time series with lower variance and values around the original data. The authors suggested combining several models and ensemble learning methods in future research. A detailed analysis of many methods is given in [16]. In this paper, authors reviewed 47 articles and 264 forecasting methods. The most promising prognostic models using the autoregressive approach, based on the review, include Fuzzy Logic, Artificial Neural Networks, Wavelet Artificial Neural Networks, Adaptive Neuro Fuzzy Inference Systems, Genetic Algorithms, Fuzzy Regression, and Data Envelope Analysis. The authors ranked forecasting models based on the mean average percentage error (MAPE). The models with the lowest value of MAPE were DEA – Data Envelopment Analysis and Fuzzy Regression [17]. Paper [18] analysed the use the random forest for short-term load forecasting. This model is easy to learn and optimize because of a small number of hyperparameters. The authors proposed a global mode of training with additional predictors representing calendar data. Paper [30] presented a comparative study of the Multi-Layer Perceptron (MLP) and Support-Vector Machine (SVM). The result showed that SVM is more suitable for classification and MLP is more appropriate for regression analysis. In the paper [19] neural networks for short-term load forecasting based on the pattern are compared: Multi-Layer Perceptron, Radial Basis Function, generalized regression neural network, fuzzy counter-propagation neural networks, and self-organizing maps. The best performance was found on generalized regression neural network. Machine learning-based models have been applied in short term demand forecasting, such as long short-term memory based LSTM [31], temporal fusion transformers-based (TFT) [20], particle swarm optimization (PSO) [21], genetic algorithms (GA) [22]. Load forecasting has been extensively applied either at the system/region level or at the building/point-of-delivery scope. Short-term load forecasting at the low voltage level, other than at the smart meter level, such as primary and secondary substations, has not been as extensive [23]. Paper [25] presents a new approach of load forecasting based on SVMD and eXtreme Gradient Boosting (XGBoost) for industrial customers. The relevant factors including operational pattern of industrial customers, environmental temperature and calendar rules are analysed. Further, the input features are optimized by feature selection tool. Finally, considering that the direction of the trend series changes plainly, the linear regression (LR) model is applied to the trend series to reduce the complexity of the model. The XGBoost regression model is introduced for each fluctuation subseries, the hyper-parameters of XGBoost are optimized by Bayesian optimization algorithm (BOA). Paper [26] presented multi-objective fruit fly optimization algorithm based on population Manhattan distance (pmdMOFOA) to optimize the operation state of the distribution network.

## Problem Formulation and Methods

*Demand forecasting*

The basic assumption of electricity demand forecasting was to determine forecasts (for each energy meter) with hourly quantization for time zones one hour before the beginning of each time zone. The forecasting was performed for three time zones (constituting 24-hour time series):

- the 8-hour time zone: from 22:00 to 6:00,
- the 7-hour time zone: from 6:00 to 13:00,
- the 9-hour time zone: from 13:00 to 22:00.

For the demand forecasting, energy consumption data from AMI system were used. 15-minute readings of consumed energy for each of the load node from AMI system were reduced to hourly values of energy consumption in load nodes. There are no energy meters for which data for all timestamps would be available. For example, in year 2018, respectively:

- number of energy meters having measurements for min. 99% of timestamps in 2018: 973 (95.5%) available,
- number of energy meters having measurements for min. 90% of timestamps in 2018: 989 (97.1%) available.

The data obtained from the AMI system were supplemented with missing values and incorrect values were removed during the process of input data correction.

The process of input data correction was performed in following steps:

1. Removing from the energy meter data those records where the value is lower than the previous one - every next value must be not lower than the previous one.
2. Creation for each energy meter, a list with the increasing sum of the profile coefficient values and enter in it the gaps corresponding to the gaps in input data from energy meters
3. Assigning the auxiliary value $diff$ corresponding to the difference of the previous and next available reading for all rows that do not have hourly consumption data.
4. For all rows with a missed value of hourly consumption $Eh$, assign a secondary value $sum\_diff$ corresponding to the difference of the previous and next available data from the list of sum of profile factors.
5. For all rows with a missed value of hourly consumption $Eh$, assign an auxiliary value $coef$ corresponding to the value of the profile factor for the given tariff group and the date and time.
6. For each missed value in the list of hourly consumption $Eh$, calculate the value of filling the gap according to the formula (1)

$$(1) \qquad Eh\,[kWh] = coef * \frac{diff}{sum\_diff}$$

where: $coef$ – value of the profile factor for the given tariff group and the date and time, $diff$ – difference of the previous and next available reading for all rows with is no hourly consumption data, $sum\_diff$ – difference of the previous and next available data from the list of sum of profile factors.

In addition, an upper $Eh$ limit of 5kWh for tariff groups G and 60 kWh for tariff groups C is introduced.

Based on historical data and weather forecasts, for each hour in the test set (2018-02-01 - 2019-01-31) (with training set 2017-01-01 – 2018-01-31), the forecast of energy consumption in the load node was calculated and compared with the readings from energy meters.

The following forecasting methods were tested:

1. Naive method:
   a. *Naive_-1d*: energy demand value for each energy meter is equal to the value for the same hour of the previous day
   b. *Naive_-1w*: energy demand value for each energy meter is equal to the value for the same hour and day of the previous week
2. *Profile*: method based on energy consumers profiles (developed by DSO).
3. *MLP*: method based on ANN, multi-layer perceptron.
4. XGBOOST:
   a. *Xgb_ind* – separate models for each load node, normalized by min-max.
   b. *Xgb_ind* – separate models for each load node, non-normalized.
   c. *Xgb_sum* - universal consumer model.
   d. *Xgb_power_peak* - universal consumer model, created for the power peak prognosis
   e. *gb_ind_power_peak* – separate models for each load node, created for the power peak prognosis

Energy consumption forecasts according to the profile method are calculated based on the table with profile factors. The data from the table are processed into a list containing the profile factors $profile\_factor$ assigned to each hour of the year in a given tariff group. For each energy meter with available data, the total energy consumption per year $coef\_year$ and as well as average hourly energy consumption $1y\_avg$ are calculated. For each hour, the profile forecast is calculated as the product of the value of the profile factor for a given hour and the quotient of the average energy consumption for a given energy meter and the average hourly value of the profile factor in the previous calendar year, according to the formula (2).

$$profile\_forecast = profile\_factor * \frac{1y\_avg}{coef\_year} \tag{2}$$

where: $profile\_factor$ – value from tariff groups profiles, $1y\_avg$ – value of the average hourly energy consumption, $coef\_year$ – value of the total energy consumption per year.

The following data was used as input for the MLP network:

1. Temperature.
2. Insolation
3. Precipitation
4. Day of the week number (from 0 to 6)
5. Hour (from 0 to 23 UTC)
6. Weekly average energy consumption
7. Energy consumption from 24 hours ago
8. Energy consumption from 168 hours ago (one week)

MLP network was trained on universal energy consumer model - data from all load nodes in the area are taken into account during training, with energy consumption normalized to the maximum value for a given load node during the learning period.

XGBoost, which stands for Extreme Gradient Boosting, is a scalable, distributed gradient-boosted decision tree (GBDT) machine learning library. It provides parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems. In the used method, separate models were built for each load node. The input data were the same as in MLP.

MLP and XGBoost was implemented using python, Keras and XGBoost.

Following quality measures were used during evaluation of methods:

- MAE corresponds to the average of MAE errors calculated for each hour for each energy meter separately [kWh], according to the formula (3),
- nMAE corresponds to the average of MAE errors calculated for each hour for all energy meters, normalized with average consumption last year [%], according to the formula (4),
- MAE_peak corresponds to the average of MAE errors calculated for peak hour for each energy meter separately [kWh],
- RMSE_peak corresponds to the average of RMSE errors calculated for peak hour for each energy meter separately [kWh], according to the formula (5),
- PSAE – nMAE normalized by energy consumption in a given month (quotient of the sum of absolute errors and the sum of consumption in a given month) [%], according to the formula (6).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i^*| \tag{3}$$

$$nMAE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - y_i^*|}{c_{norm}} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^*)^2} \tag{5}$$

$$\mathrm{PSAE}_{node} = \frac{\sum_{t=0}^{h} Abs\_err_t}{\sum_{t=0}^{h} E\_real_t} \tag{6}$$

where: $n$ – number of load nodes, $y_i$ – predicted value, $y^*_i$ – true value, $cnorm$ – value of average energy consumption in the year, $Abs\_errort$ – sum of absolute errors in one month, $E\_realt$ is sum of energy consumption in one month, $h$ is the hours number in one month.

*Configuration optimization*

The task of optimal grid configuration is defined as follows:

the optimal cut-off locations in the MV and LV distribution grid should be so determined, as to minimize the total cost of power and energy losses in a given optimization period, subject to the required constraints. The set of constraints is divided into two groups:

1. Reliability constraints
   a. The network type is retained (all consumers' electricity supply is assured, no consumer is two-sided supplied),
   b. The set of arbitrarily disconnected arcs is retained.
2. Technical constraints
   a. The allowable voltage drops are retained,
   b. No grid element is overloaded.

In the power-flow algorithm only reliability constraints are controlled. The solution to the task is based on its specific properties.

The following objective function (7) was defined for the AG method, as the total cost of the power and energy losses:

$$K_{loss} = \sum_{j=1}^{n}\left(\Delta P_j k_p + \Delta Q_j k_q + \Delta A_j k_A\right) \tag{7}$$

where: $K_{loss}$ – power loss cost, $n$ – number of arcs in the network, $\Delta P_j$ – active power loss in the arc $j$, $k_p$ – unit cost of active power, $\Delta Q_j$ – reactive power loss in the arc $j$, $k_q$ – unit cost of reactive power, $\Delta A_j$ – loss of active energy in the optimization period $T$ in the arc $j$, $k_A$ – unit cost of active energy.

Heuristic power-flow algorithm [5] is an approximate method, in its subsequent steps the least loaded lines are disconnected, while controlling the compliance with technical specifications. The power-flow algorithm's operating principle is as follows:

1. The grid is closed (statuses of the arcs that can be closed are set to "closed"), equal voltages are assumed across all nodes which are supply points.
2. The current or active power flow is determined (using DC algorithms), the cut-off is allocated to the least loaded line, the compliance with technical requirements is controlled. If the cut-off results in loss of the grid's integrity, the next line in terms of current or active power flow is eliminated.
3. This procedure continues until a tree type grid is obtained.

For each analysed period, calculations were done for three time zones for each 24 hours. Time zones were defined based on the multi-zone tariff and are the same as for forecasting problem.

The result are statuses of switches for each of the three time zones of the day. Calculations were performed for forecasted values of energy consumption and recalculated using real energy consumption taken from AMI system.

Using heuristic power-flow algorithm, the optimal configuration was searched for the hour with the highest network load in each time zone. Energy losses for the whole analysed period were calculated only for the final optimal network configuration.

In the case of genetic algorithm, energy losses for the whole analysed time zone were calculated for each network configuration which state for one individual in each population.

Energy losses were calculated for the whole time zone using peak energy losses duration, determined separately for each area supplied from MV/LV transformer station.

Table 1. MAE, nMAE and MSE for analysed forecast methods.

| method | hours | MAE | nMAE | RMSE | MAE peak | RMSE peak |
|---|---|---|---|---|---|---|
| | | [kWh] | [%] | [kWh] | [kWh] | [kWh] |
| xgb_ind | 0-24 | 0.759 | 12.60% | 1.507 | n.a. | n.a. |
| profile | 0-24 | 1.674 | 26.50% | 7.012 | n.a. | n.a. |
| naive_-1w | 0-24 | 0.934 | 16.1% | 2.785 | n.a. | n.a. |
| naive_-1d | 0-24 | 0.96 | 16.6% | 2.801 | n.a. | n.a. |
| xgb_ind | 22-6 | 0.466 | 7.70% | 0.56 | 0.635 | 0.926 |
| Xgb_power_peak | 22-6 | n.a. | n.a. | n.a. | 0.661 | 0.954 |
| xgb_ind_power_pea k | 22-6 | n.a. | n.a. | n.a. | 0.794 | 1.115 |
| profile | 22-6 | 1.27 | 21.10% | 5.913 | 1.597 | 2.513 |
| naive_-1d | 22-6 | 0.524 | 8.70% | 0.906 | 0.783 | 1.2 |
| naive_-1w | 22-6 | 0.493 | 8.20% | 0.984 | 0.689 | 1.073 |
| xgb_ind | 6-13 | 0.909 | 15.10% | 2.028 | 1.067 | 1.695 |
| xgb_power_peak | 6-13 | n.a. | n.a. | n.a. | 1.052 | 1.776 |
| xgb_ind_power_pea k | 6-13 | n.a. | n.a. | n.a. | 1.157 | 1.849 |
| profile | 6-13 | 1.829 | 30.40% | 8.468 | 1.964 | 3.388 |
| naive_-1d | 6-13 | 1.124 | 18.70% | 3.632 | 1.235 | 2.168 |
| naive_-1w | 6-13 | 1.302 | 21.60% | 6.004 | 1.47 | 2.908 |
| xgb_ind | 13-22 | 0.904 | 15.00% | 1.907 | 1.144 | 1.738 |
| Xgb_power_peak | 13-22 | n.a. | n.a. | n.a. | 1.07 | 1.676 |
| xgb_ind_power_pea k | 13-22 | n.a. | n.a. | n.a. | 1.164 | 1.754 |
| profile | 13-22 | 1.916 | 31.80% | 7.945 | 2.768 | 3.886 |
| naive_-1d | 13-22 | 1.153 | 19.10% | 3.361 | 1.327 | 2.208 |
| naive_-1w | 13-22 | 1.117 | 18.50% | 3.46 | 1.306 | 2.336 |

## Results

*The test network*

Optimization of the network configuration was carried out for a selected area of the LV network, which includes 44 sections of LV cable lines with a total length of 4697.5 m. The LV network is powered by 7 MV/LV transformers connected by MV cable lines. The LV network supplies 28 receiving nodes (residential buildings). For each of the load nodes, data on hourly electricity consumption for a period of 1 year was available.

The maximum load of the entire selected LV grid area (average 1-hour power) was 328.44 kW and the minimum load was 69.21 kW. All transformers were additionally loaded with the loads located outside the analysed part of the network supplied from these transformers. There were 136 switches in the LV network and 9 in the MV network. Only the states of switches in the LV network were subject to optimization. The map of selected area is shown on fig.1. The LV network supplies 28 load nodes, mainly residential buildings. For each of the load nodes, data on 15-minutes electricity consumption for a period of 1 year was available from AMI system.

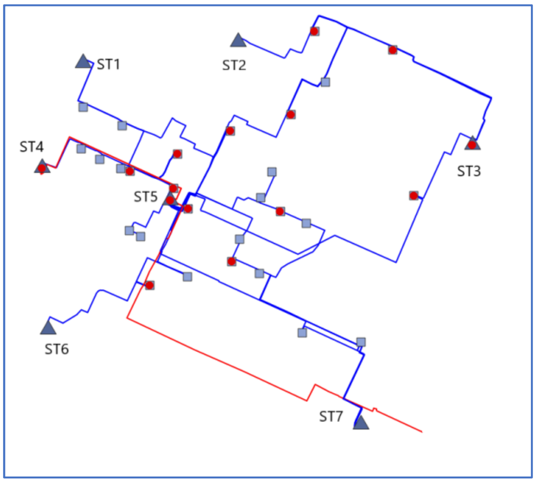


Fig. 1. The map of test network.

Table 2. The accuracy of the XGB_ind prediction by load nodes

| Node ID | Number of energy meters | % of available hourly readings | Type | PSAE [%] |
|---|---|---|---|---|
| 1 | 2 | 99.93% | Hydrophore | 18.36% |
| 2 | 96 | 98.26% | Residential | 8.84% |
| 3 | 96 | 78.25% | Residential | 7.65% |
| 4 | 52 | 89.55% | Residential | 11.14% |
| 5 | 25 | 99.92% | Small shop | 18.44% |
| 6 | 95 | 96.15% | Residential | 8.29% |
| 7 | 25 | 98.77% | Residential | 15.55% |
| 8 | 92 | 96.74% | Beauty salon | 7.69% |
| 9 | 3 | 98.61% | Hydrophore | 20.43% |
| 10 | 20 | 96.71% | Residential | 16.23% |
| 11 | 5 | 62.02% | School | 30.34% |
| 12 | 21 | 99.91% | Residential | 14.77% |
| 13 | 19 | 83.15% | Residential | 12.50% |
| 14 | 26 | 50.03% | Residential | 12.17% |
| 15 | 14 | 48.19% | Residential | 13.83% |
| 16 | 21 | 43.46% | Residential | 9.16% |
| 17 | 20 | 42.72% | Residential | 11.19% |
| 18 | 27 | 92.54% | Residential | 17.87% |
| 19 | 93 | 98.23% | Residential | 7.67% |
| 20 | 21 | 99.79% | Residential | 15.16% |
| 21 | 20 | 99.92% | Residential | 15.99% |
| 22 | 21 | 99.06% | Residential | 5.39% |
| 23 | 31 | 96.98% | Small shop | 12.29% |
| 24 | 32 | 99.53% | Residential | 13.75% |
| 25 | 1 | 99.77% | Small shop | 37.27% |
| 26 | 5 | 99.90% | Small shop | 17.12% |
| 27 | 2 | 88.34% | Kindergarten | 26.72% |
| 28 | 3 | 86.74% | Church | 38.11% |

*Demand forecast*

Errors for analysed methods are given in the tables 1, 2. The demand forecast and real demand for chosen cases are shown on fig. 2, 3 and 4. For load nodes (group of energy consumers) XGBoost method was chosen.

*Network configuration optimization*

The network configuration optimization results are shown in table 3. The results for optimization for whole 2018 year are given in table 4. Optimization result is the one network configuration for whole year. The energy losses were calculated using duration of maximum losses, calculated for each MV/LV transformer station separately.

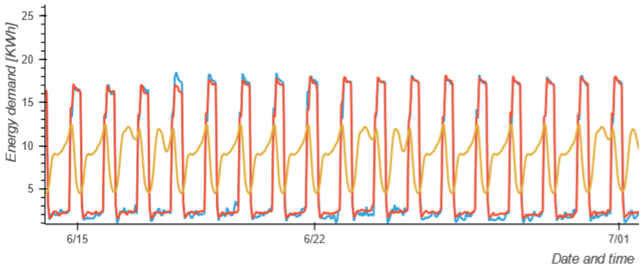


Figure 2. Forecast (red line) for a node with regular energy consumption (blue line). (orange line - downscaled consumption for all nodes)

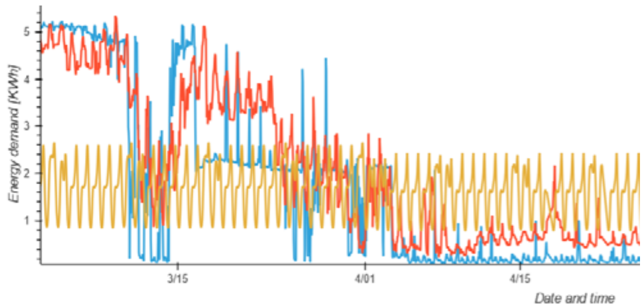


Figure 3. Very uneven nature of consumption making forecasting difficult – the hydrophore. (red line – forecast; blue - real consumption; orange - downscaled real consumption for all nodes)

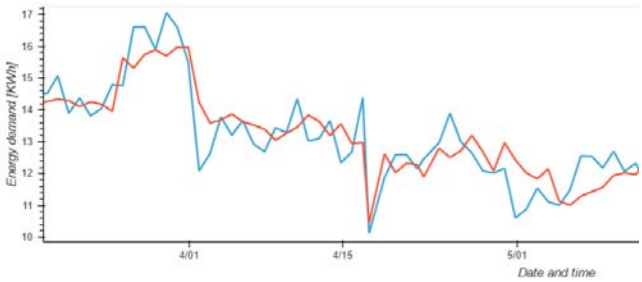


Figure 4. Forecast (red) for sum of loads (daily quantization)

**Discussion**

Optimization was carried out for forecasts - that is, in reality, greater reductions of losses are usually obtained than those determined in the optimization processes.

Results of the optimization for 3 time zones during the day (the time zones are defined based on tariffs) shows that genetic algorithm gives better results for forecasted demand. However, in the next step of analysis, the optimum network configurations were verified using real power demands values for nodes.

Optimization for one day: genetic algorithm is better than heuristic for both the minimum load day and the maximum load day. For the day with maximum load, the heuristic algorithm did not reduce the amount of energy losses in relation to the initial configuration of the network, reducing only very slightly power losses in the hour of peak load.

Generally, genetic algorithm is better taking into account forecasted energy demand, however after recalculating optimization results using real energy demands values, the heuristic algorithms gives better results.

There are some hard to predict loads in analyzed area. There are three load nodes that have definitely higher forecast error. Generally real energy losses are greater than prognosed, average absolute error for the year is 15,31%, maximum absolute error 61% and minimum absolute error 0,0%.

For the heuristic algorithm it is important to forecast maximum demand value in the analyzed time zone. The heuristic algorithm is looking for optimum solution using only values of current in networks element, so they should be taken from the set of maximum values occurring in the analyzed period.

In the case of genetic algorithm, the power flow calculations for each hour during the analyzed time zone gives more precise energy losses than calculation energy losses using duration of maximum losses. However, the number of power flow calculations must be multiplied by number of hours in analyzed time zone. In presented paper, AG population size was taken as 20 and generations number as 25, so there were performed 500 power flow calculations. In the case of energy losses calculation for each hour during the analyzed time zone, it can be even 4500 power flow calculations for a given example and 9-hour time zone. For the greater analyzed network, the population size must be of course greater, so there will be greater number of power flow calculation in the case of using genetic algorithm.

Table 3. Calculation results for different periods.

| | Before Optimisation | | HEURISTIC | | GENENTIC | |
|---|---|---|---|---|---|---|
| | AMI | FORECAST | AMI | FORECAST | AMI | FORECAST |
| PERIOD - 24.06.2018 - one day, high demand, three time zones | | | | | | |
| REAL ENERGY [kWh] | 18508.04 | 18306.03 | 18501.76 | 18303.77 | 18503.83 | 18301.80 |
| REAL ENERGY LOSSES [kWh] | 193.266 | 169.651 | 186.98 | 167.39 | 189.06 | 165.42 |
| ENERGY LOSSES [%] | 1.04% | 0.93% | 1.01% | 0.91% | 1.02% | 0.90% |
| ENERGY LOSSES REDUCTION [kWh] | | | 6.284 | 2.261 | 4.208 | 4.231 |
| ENERGY LOSSES REDUCTION [%] | | | 3.25% | 1.33% | 2.18% | 2.49% |
| PERIOD - 23-30 06.2018 – one week, three time zones | | | | | | |
| REAL ENERGY [kWh] | 136147.2 | 134562.1 | 136101.1 | 134539.2 | 136129.7 | 134532.1 |
| REAL ENERGY LOSSES [kWh] | 1418.5 | 1278.8 | 1372.4 | 1255.9 | 1401.0 | 1248.8 |
| ENERGY LOSSES [%] | 1.04% | 0.95% | 1.01% | 0.93% | 1.03% | 0.93% |
| ENERGY LOSSES REDUCTION [kWh] | | | 46.091 | 22.845 | 17.478 | 29.957 |
| ENERGY LOSSES REDUCTION [%] | | | 3.25% | 1.79% | 1.23% | 2.34% |

| | Before Optimisation | | HEURISTIC | | GENENTIC | |
|---|---|---|---|---|---|---|
| | AMI | FORECAST | AMI | FORECAST | AMI | FORECAST |
| PERIOD - 24.06.2018 - one day, high demand, three time zones | | | | | | |
| PERIOD 12.2018 – one month, three time zones | | | | | | |
| REAL ENERGY [kWh] | 779478.5 | 769314.1 | 779045.1 | 768967.1 | 779247.0 | 769061.5 |
| REAL ENERGY LOSSES [kWh] | 8517.7 | 7645.3 | 8084.2 | 7298.3 | 8286.2 | 7392.7 |
| ENERGY LOSSES [%] | 1.09% | 0.99% | 1.04% | 0.95% | 1.06% | 0.96% |
| ENERGY LOSSES REDUCTION [kWh] | | | 427.798 | 428.798 | 431.798 | 432.798 |
| ENERGY LOSSES REDUCTION [%] | | | 5.02% | 5.61% | 5.07% | 5.66% |
| PERIOD 06.2018 – one month (minimum energy demand), three time zones | | | | | | |
| REAL ENERGY [kWh] | 602457.2 | 592480.1 | 602239.4 | 592376.9 | 602349.6 | 592350.8 |
| REAL ENERGY LOSSES [kWh] | 6277.7 | 5447.9 | 6059.9 | 5344.7 | 6170.1 | 5318.6 |
| ENERGY LOSSES [%] | 1.04% | 0.92% | 1.01% | 0.90% | 1.02% | 0.90% |
| ENERGY LOSSES REDUCTION [kWh] | | | 217.754 | 103.257 | 107.595 | 129.31 |
| ENERGY LOSSES REDUCTION [%] | | | 3.47% | 1.90% | 1.71% | 2.37% |

Table 4. Calculation results for the whole year, without time zones.

| | Before opt. | HEUR | GEN |
|---|---|---|---|
| REAL ENERGY [kWh] | 8102863.2 | 8101690.5 | 8101476.3 |
| REAL ENERGY LOSSES [kWh] | 68589.1 | 67416.3 | 67202.2 |
| ENERGY LOSSES [%] | 1.09% | 0.84% | 0.84% |
| LOSSES REDUCTION [kWh] | | 1172.7 | 1386.9 |
| ENERGY LOSSES REDUCTION [%] | | 1.71% | 2.02% |
| NUMBER OF SWITCH STATUS CHANGES | | 20 | 18 |

**Conclusions**

The optimization of the network configuration was performed for a specific period. In the case of optimizing the configuration of the distribution network with a heuristic algorithm, it is important to forecast the load peaks in the best possible way during the period for which the optimization is performed. In general, the actual power and energy losses in the distribution network are higher than the losses determined on the basis of the forecasted loads. The heuristic algorithm is much faster than the genetic algorithm. In a situation where the allowable calculation time is very short (e.g. calculation after a failure), the use of a heuristic algorithm is justified. Base heuristic algorithm requires one power flow calculation for the beginning and one on the end to calculate power losses reduction. As it has been presented for test network differences between results given by genetic and heuristic algorithms are small. In addition, the genetic algorithm produced results with fewer switches state changes required. For larger, more complicated, and overloaded networks differences will be probably higher.

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