# Two stage approach to optimize electricity contract capacity problem for commercial customers

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**Abstract.** The electricity tariffs available to Polish customers depend on the voltage level to which the customer is connected as well as contracted capacity in line with the user demand profile. Each consumer, before connecting to the power grid, declares the demand for maximum power which is considered a contracted capacity. Maximum power is the basis for calculating fixed charges for electricity consumption. Usually, the maximum power for the household user is controlled through a circuit breaker. For the industrial and business users the maximum power is controlled and metered through the peak meters. If the peak demand exceeds the contracted capacity, a penalty charge is applied to the exceeded amount which is up to ten times the basic rate. In this article, we present a solution for entrepreneurs which is based on the implementation of two stage approach to predict maximal load values and the moments of exceeding the contracted capacity in the short-term, i.e., up to one month ahead. The forecast is further used to optimize the capacity volume to be contracted in the following month to minimize network charge for exceeding the contracted level. As shown experimentally with two datasets, the application of multiple output forecast artificial neural network model and genetic algorithm for load optimization delivers significant benefits to the customers.

**Keywords:** contracted capacity, optimization, genetic algorithm, electricity load time series forecasting.

## 1 Introduction

Energy storage and supply conditions are demanding and difficult on the electricity market when compared to other inputs of a typical production system. Therefore, forecasting the load demand is of high importance. To deal with those inconvenient conditions, energy producers propose different energy tariffs and contract options to their customers. Usually, voltage level and individual contracted capacity are the main factors to assign proper tariff. This strategy ensures that fluctuations in energy demand are controlled, what gives an insight for the energy quantity required to be generated and allows to transmit it to the customers.

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The Polish demand side of the retail electricity market comprises end-users. In total, there are over 17.05 million of them, out of whom 90.3% (15.4 million) are the customers in G tariff group, with a great majority of household consumers (over 14.5 million) who purchase electricity for individual consumption [1]. The rest of end-users are industrial, business and institutional clients and they may belong to A, B or C tariff group [2]. There are three voltage levels distinguished in Poland: high voltage (110 kV and higher), medium voltage (higher than 1 kV but lower than 110 kV) and low voltage (less than 1 kV). Tariff groups A and B comprise customers supplied from the high and medium voltage grids, i.e., the so-called industrial customers, whereas group C is typical for the customers connected to the. low voltage grid consuming electricity for the purpose of small and medium business activity.

One of the main variables considered in the tariff structures is the capacity component so the users are charged for the availability to use the maximum power, in line with the connection agreement which is the maximum value of the averaged consumed power within the period of 15 minutes in an hour span [3]. In practice, households and small business are not obliged to monitor the level of power consumed on an ongoing basis. Customers who are using these tariffs are not charged for exceeding the contracted capacity. On the other hand, if the declared capacity quantity is exceeded by the consumer of tariff groups (C, B or A) penalty charge is levied. In line with the government's regulation with regards to the specific rules for the determination and calculation of the tariffs and billing in electricity industry [3], a fee is charged for exceeding the contractual capacity defined in the contract. The fee constitutes the product of the rate of capacity charge and the sum of ten largest quantities of the surplus consumed capacity over the contractual capacity, indicated by the measuring and clearing device or ten times the maximum amount of surplus of consumed capacity over the contracted capacity recorded during the reference period.

Large companies which are connected to medium or high voltage lines, usually have an energy specialist who takes care of the energy consumption parameters and supervises them on an ongoing basis. The level of power consumed is monitored by the metering systems, and in case of exceeding the contractual level, an additional fee related to exceeding value appears on the invoice. In practice, big companies are rarely unconscious about exceeding their contractual capacity. On the other hand, entrepreneurs operating in the field of services, production and processing, who are connected to low voltage with contracted capacities above 40 kilowatts [3], do not always have the time, appropriate information, and knowledge to control their energy consumption parameters to ensure their optimal adjustment. Generally, in order to avoid over-contracted capacity amount, customers declare a level of contracted capacity that is much higher than their needs. On the other hand, those customers who are not using the planned capacity pay for the unused power.

**Time horizon selection**. Numerous papers consider load forecasting, but only few of them use the short-term load forecasting for tariff optimization. Most of the works are mainly related to long-term optimization of the electricity purchase and distribution process by suppliers and distributors. In general, load forecasting has been investigated by utilities and electricity suppliers where Long-Term Load Forecasts (LTLF) are used

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to predict the annual peak of the power system [4, 5] in order to manage future investments in terms of modernization and launching new units to maintain stability of nationwide electricity demand over time periods of up to 20 years [6]. The Medium-Term Load Forecasts (MTLF) use hourly loads to predict the weekly peak load for both, power and system operations planning [7]. The Short-Term Load Forecasts (STLF) usually aim to predict the load up to one-week ahead, while the Very Short-Term Load Forecasts (VSTLF) are used for a time-horizon of less than 24 hours. Both, STLF and VSTLF have engaged the attention of most researchers, since they provide necessary information for the day-to-day utilities' operations [8]. These forecasts become also useful when dealing with smart grid, micro grids, peak load anticipation, and intelligent buildings [9, 10].

**STLF techniques**. There are number of papers dedicated to short-term load forecasting of the commercial customers for the purpose of contract capacity optimization. Also, there are numerous approaches applied to load forecasting with good accuracy. Importantly, the quality of the forecast improves when the forecasting is applied to the higher aggregation levels (like group of customers, power stations or cities) and this can be achieved with quite low errors. In the earliest works, some classical techniques including auto regression (AR) models [11], linear regression models [12], dynamic linear and nonlinear models, general exponential smoothing models, spectral methods, and seasonal ARIMA models were used for forecasting[13-15]. Unfortunately, their capability to solve time series with complex seasonality and non-linear series is limited, in favor of artificial neural networks (ANN) techniques and expert systems [16 -19]. Interestingly, load forecasting field is one of the most successful applications of ANN in power systems. Neural networks are able to deliver better performance when dealing with highly non-linear series resulting from e.g. the non-integer seasonality appearing as a result of averaging ordinary and leap years.

**Optimization**. Various types of hardware and software solutions. Load limiters [20] are currently used to prevent overruns. Another, more sophisticated option like Electric Power Distribution and Utility Monitoring System provided by [21] support large and medium-sized sites in Japan in terms of energy efficient management, preventive maintenance and capacity overruns. A measurement data screen is provided to display real-time measurement data which alarms if the predicted demand exceeds the present level. Then actions can be taken automatically or manually.

For small companies a simple and uncomplicated solutions using e.g. Excel are applicable to analyze the relation between the contracted capacity and the actual consumption. When contracted capacity levels are exceeded, they have then the ability to increase the level of contracted capacity or change the structure of energy consumption. As a result of the analysis, the client can reduce consumption in periods when the capacity is exceeded and increase consumption in periods when there is a capacity reserve. Unfortunately, these solutions are ineffective because they are based on the monthly averaged data from the electricity consumption invoices, while the excess of power is determined based on averaged data recorded over 15-minute periods. More effective solutions for contracted capacity optimization can be achieved using different models including deep learning neural networks [22], Particle Swarm Optimization

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(PSO)[23], Genetic Algorithm (GA) [24] or Linear Programming (LP) optimization [25].

Motivated by aforementioned discussions, this paper presents solution for small and medium-sized enterprises from the C tariff group, concerning short-term load forecasts as a basis for calculating and optimizing the capacity required to avoid any additional fee related to exceeding contracted capacity level.

Specifically, Long Short-Term Memory (LSTM) Artificial Neural Network (ANN) is constructed to forecast the load values and the moments of exceeding the contracted capacity in the short-term horizon, i.e., up to one month ahead. The forecast is further used to optimize the capacity volume to be contracted in the following month for the commercial customer to minimize network charge for exceeding the contracted level.

Long Short-Term Memory networks belong to a complex area of deep learning methods. These are type of recurrent neural network (RNN) capable of learning order dependence in sequence prediction problems like time series. The reason for using recurrent networks is that these are different from traditional feed-forward neural networks and, in addition to the complexity and volatility in electricity time series, comes with the expectation to reveal new patterns and behaviors that the traditional methods cannot achieve [26, 27]. Standard RNNs often fail to learn correctly in the presence of time lags greater than 5 – 10 discrete time steps between the input events and target signals. The problem with disappearing error raises question whether standard RNNs can indeed provide significant practical advantages over time window-based feedforward networks. As provided in [28], LSTM model is not affected by this problem and it can learn to bridge minimal time lags in excess of 1000 discrete time steps by enforcing constant error flow through "constant error carrousels" (CECs) within special units, called cells.

The remainder of this paper is organized as follows. Section 2 proposes two stage approach to optimize electricity contract capacity problem. First stage presents multiple output strategy for forecasting supported by LSTM ANN model. The second stage uses genetic algorithm to optimize the electricity contract capacity. Section 3 provides a detailed description of the tariff structure in Poland. Section 4 applies the models to real datasets for two commercial customers in Poland. Section 5 concludes with the comments and provides directions for the future research.

## 2 Two stage approach to optimize electricity contract capacity problem

### 2.1 Stage one – LSTM electricity load time series forecasting

Time series forecasting is typically considered as one-step prediction. Due to the fact that electricity load forecasting is essential for both, the utility and the customer, it cannot be designed with one step prediction. Maximum power is used by the utility to provide the right amount of power for customers, whereas it is the basis for calculating, usually monthly, fixed charges for the industrial and business electricity users. Predicting multiple time steps is considered a multi-step forecasting and it includes prediction

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of the load values [L+1, …, L+t] of historical load time series [L1 ,…., LN] composed of N load observations, where t>1 denotes the forecasting horizon. In this paper we used multiple output strategy for forecasting which involves the development of a single model that is capable of predicting the entire forecast time horizon in a one-shot approach. Therefore, to predict load required for the next e.g. two data points, we would develop one model and use it to predict the next two data points as one operation. The model form would be as follows:

L_prediction(t+1), L_prediction(t+2) = model1(L (t-1), L (t-2), ..., L (t-n))

The model can learn the dependence structure between inputs and outputs as well as between outputs. Specifically, for this approach, the LSTM Artificial Neural Networks were constructed to forecast the load values and the moments of exceeding the contracted capacity in the short-term horizon, i.e., up to one month ahead and hour by hour. The forecast is further used to optimize the capacity volume to be contracted in the following month for the commercial customer to minimize network charge for exceeding the contracted level.

Additionally, the naive forecast was considered in the following manner: for the forecasting horizon, the values observed for the same hour and same day of the four previous week were averaged and taken as a forecast. However, the forecasts were far from the optimal and therefore, these were not further optimized.

### 2.2 Stage two – load forecast optimization

In this article, we consider peaks over contracted capacity in a given month. Most customers order the same amount of power for individual months of the year. If the peak demand does not exceed the contractual capacity, a fixed capacity charge will be levied. It constitutes the product of the fixed capacity rate R [PLN/kW], where PLN stands for Polish Zloty and contracted capacity demand for month Rt in kW. For exceeding the contractual capacity defined in the contract an additional surcharge for excess demand will be added. The annual fee per year can be, therefore, expressed as:

$$Cost_m = \begin{cases} R_m * d_m & d_m < d_m^c \\ R_m * d_m + R_m * (d_m - d_m^c) * n_m & d_m^c < d_m \end{cases} \quad (1)$$

$$Cost_{total} = \sum_{m=1}^{\text{year}} Cost_m \quad (2)$$

where
$d_m^c$ – contracted capacity (kW) in month m;
$d_m$ – maximum demand amount (kW) in month m;
$n_m$ – the sum of up to ten largest amounts of surplus consumed capacity over the contractual capacity, indicated by the measuring.
$R_m$ – rate of contractual capacity (PLN/kW) in month m.

In this work, since 12 months of data us available, we consider the total cost over 10 months, i.e., March–December 2016, due to the fact that January and February were

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considered for model training (including variable calculations with delays). The solution that minimizes the annual total contracted capacity cost and the penalties for excessive consumption over the fixed capacity amount can be solved using Particle Swarm Optimization, Genetic Algorithm (GA) or even the Excel's solver for linear programing. However, in this paper we propose GA which can find multiple Pareto solutions for a multi-objective optimization problem in one run.

In principle, genetic algorithms are stochastic search algorithms inspired by biological evolution and natural selection processes. GAs simulate the evolution process where the fittest individuals dominate over the weaker ones, by reflecting the biological mechanisms of evolution, such as selection, crossover and mutation. For the experiments we used R package for GA as it provides a collection of various functions for optimization using genetic algorithms. The package includes a flexible set of tools for implementing genetic algorithms search in both the continuous and discrete case, whether constrained or not. Several genetic operators are available and can be combined to explore the best settings for the analyzed problem. Basically, the default parameters settings were used to maximize a fitness function using genetic algorithms in line with documentation [https://cran.r-project.org/web/packages/GA/GA.pdf]

## 3 Data characteristics and tariff structure

There were two separate data sets used in the analysis. Each data set consists of data points at 15 minutes intervals gathered for medium-size commercial customers and covering time interval time between January 1st, 2016 and December 31st, 2016. In total, there are 35 136 observations in each data set. The customers belongs to C tariff group which is applicable to small and medium-size enterprises where the electricity is supplied with low voltage lines. The group includes C2x tariffs where contracted capacity is over 40 kilowatts and the letter "x" designates the number of energy consumption zones per day. The following tariffs are available: C22a tariff with two-zones measurement (peak and off-peak), C22b tariff with two-zones measurement (day and night) and C23 tariff with three zones measurement per day.

The first data set contains details for the customer who belongs to C22a tariff. The customer is classified as a small pharmaceutical plant with a contracted capacity greater than 40 kilowatts and who is mainly using electricity during the day hours. The contracted capacity for the customer is 51 kW. Fig. 1a shows lower electricity consumption during morning and evening peak hours. Much higher consumption is observed between 10:00 and 16:00. The second data set contains details for the customer who belongs to C22b tariff. It is a confectionery plant which performs majority of its activities during the night. The contracted capacity for the customer is 80 kW. Fig. 1b shows lower electricity consumption in the daytime zone, i.e., between 6:00 and 21:00 and higher consumption in the night time zone, between 21:00 and 6:00.

Most of the users within C2x tariff groups, do not possess detailed usage data to control energy consumption parameters and to ensure their optimal adjustment. As shown on Fig. 2. the contracted capacity is not adequately set as it is often being exceeded in the reality. On the other hand, average load consumption does not exceed

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70% of the contracted capacity level, which translates into losses due to unused capacity. Therefore, it is crucial to determine the optimal contract capacity for each month so as to minimize the total cost of the electricity bills.

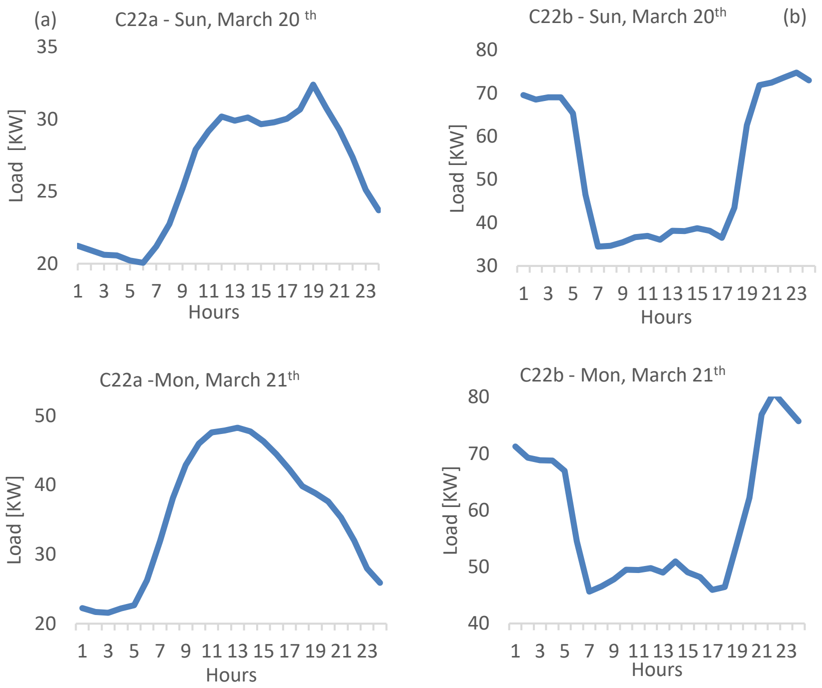


**Fig. 1.** Daily and weekly energy consumption structures of two different users: (a) user C22a, (b) user C22b.

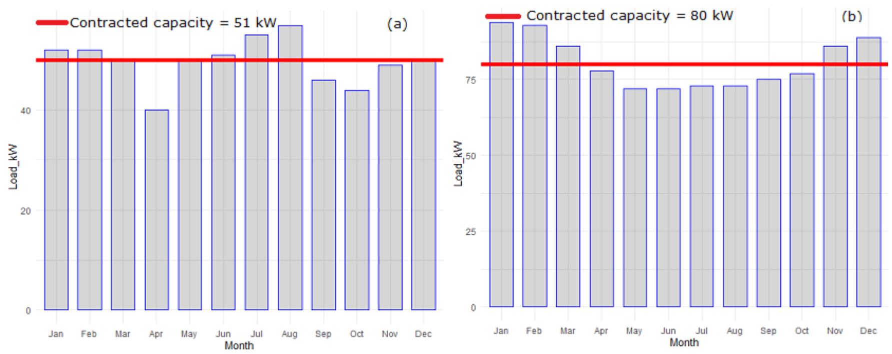


**Fig. 2.** Consumed load and contracted capacity (a) for customer C22a and (b) customer C22b.


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# 4 Numerical experiments

In this section, we use the multiple output forecast approach for electricity load forecasting as outlined in Section 2.1, and then, as the second stage, we apply genetic algorithm to optimize the user's contract capacity.

At the beginning, we start with hourly forecasts month by month through the entire year. Although the settlement with the power plant or electricity supplier is made on the basis of the monthly characteristics (including frequency and the volume of peaks), the hourly forecast is necessary for load optimization at second stage. These values constitute the input data to predict and then optimize the amount of capacity required in the next monthly period.

For the forecasting approach we determine the following components: (1) The quantities and costs incurred on the basis of the actual load consumptions and contract capacity, i.e., the constant value declared by the user at the beginning of the contract period; (2) The optimal load amount and the cost that user would incur. This is the case when we know, in advance, the amount of power required at the end of the billing period. (3) The optimal amount and the costs that user would incur on the basis of the predicted load quantities using a LSTM neural network. Ultimately, we determine the optimal contract capacity using a genetic algorithm.

**The capacity contract optimization**

We used the Multiple output forecast strategy with ANN to predict the contract value with the maximum consumption values as well as the maximum load at specific hours and days of the week. These values were used further as the input to the genetic algorithm in order to establish such monthly contract capacity values that would help the user to avoid charges for exceeding the contracted level. The analysis were carried out for q100 quantile in order to check how large the maximum loads are and based on those, we searched for the optimal contract values using the genetic algorithm. The loss in Quantile Regression for an individual data point is defined as:

$$\mathbb{Q}(\varsigma_i|\alpha) = \begin{cases} \alpha\varsigma_i, & if\ \varsigma_i \ \geq 0 \\ (\alpha-1)\varsigma_i\,, & if\ \varsigma_i \ < 0 \end{cases} \tag{3}$$

where alpha is the required quantile (a value between 0 and 1) and

$$\varsigma_i = y_i - f(x_i) \tag{4}$$

where f(x) is the predicted (quantile) model and y is the observed value for the corresponding input x.

At the following the results of the forecasting experiments and optimization will be discussed. The following notations are used in the Tables 1–2:

- Actual contract – the value of the customer's contracted capacity in kW;
- Actual cost – the customer's total cost of contracted capacity and the penalties of exceedances the contracted capacity level in PLN;
- Above actual contract – the number of loads consumed over the contracted level in kW;

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- Opt contract capacity – the optimal amount of consumed capacity based on the historical usage in kW;
- Opt contract cost – the optimal cost of consumed capacity based on historical usage in PLN;
- Above opt contract – the number of loads over the contracted capacity based on historical usage;
- Opt contract capacity pred – the optimal contract based on the forecast obtained by neural network and optimized by GA in kW;
- Opt cost capacity pred – the total cost of optimal contract predicted by the network and optimized by GA in PLN;
- Above opt capacity pred – the number of loads over the contracted capacity based on the forecast obtained by neural network and optimized by GA.

**Table 1.** Multiple output forecast strategy with Q100 for C22a tariff user.

| Actual values | | | | Optimal values based on historical usage | | | Optimal values based on predicted usage | | |
|---|---|---|---|---|---|---|---|---|---|
| Month | Actual contract [kW] | Actual cost [PLN] | Above actual contract | Opt contract capacity [kW] | Opt contract cost [PLN] | Above Opt contract | Opt contract capacity pred [kW] | Opt cost capacity pred [kW] | Above opt capacity pred |
| Mar | 51 | 510 | 0 | 50 | 506.74 | 1 | 53 | 530 | 0 |
| Apr | 51 | 510 | 0 | 47 | 471.39 | 1 | 49 | 490 | 0 |
| May | 51 | 510 | 0 | 50 | 501.72 | 1 | 51 | 510 | 0 |
| Jun | 51 | 522.89 | 2 | 52 | 520 | 0 | 52 | 520 | 0 |
| Jul | 51 | 950.3 | 122 | 56 | 560 | 0 | 56 | 560 | 0 |
| Aug | 51 | 1123.16 | 95 | 57 | 571.31 | 1 | 57 | 571.31 | 1 |
| Sep | 51 | 510 | 0 | 49 | 490 | 0 | 54 | 540 | 0 |
| Oct | 51 | 510 | 0 | 46 | 466.28 | 2 | 48 | 480 | 0 |
| Nov | 51 | 510 | 0 | 50 | 500 | 0 | 50 | 500 | 0 |
| Dec | 51 | 510 | 0 | 50 | 506.52 | 3 | 51 | 510 | 0 |
| Total | | 6166.36 | | | 5093.99 | | | 5211.31 | |

Table 1 shows the results of the analysis for the customer who belongs to C22a tariff group, having a contracted capacity of 51 kW per month. During June-August period the customer consumed more capacity and therefore, the contracted level was exceeded several times in those months, even 122 times in July, what significantly increased the cost. In total, the actual cost for the customer between March and December was 6166.37 PLN. With a retrospective analysis, based on historical usage, one could see that the optimal values for contracted capacity would vary between 46 kW and 57 kW, depends on the month, as presented in the Table 1. Knowing that, the customer could benefit from lower bills, so the cost of the optimal contract would be 5093.99 PLN, which is 17.4% less than actual cost. Of course, for the customer it is difficult to specify correctly what would be the capacity required in the following months, therefore the optimal contract capacity should be forecasted. In our case we used multiple output forecast strategy with LSTM neural network to estimate maximum load for each hour and these values were used further as the input to the genetic algorithm the forecast for the optimal contract level so the total cost is minimized. As the result the forecasted capacity was between 48 kW and 57 kW, depends on the month. Importantly, only

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once, in August we would exceed the contracted capacity. This helped to keep the total cost very low, i.e., close to the optimal cost values. Eventually, the total cost of optimal contract predicted by the network and optimized by genetic algorithm was 5211.32 PLN which is very close to the optimal one (5093.99 PLN). In comparison to the actual cost, the benefit of the customer is quite material and amounts to 955.05 PLN (6166.37 – 5211.32) which is 15.5% of the actual bills.

In the similar manner the analysis for the second customer was prepared. Table 2 shows the results of the analysis for the customer who belongs to C22b tariff group, having a contracted capacity of 80 kW per month. During March, November and December the customer consumed more capacity and therefore, exceeded the contracted level many times, specifically even 266 times in December, what significantly impacted the actual bills. In total, the actual cost for the customer between March and December was 10789.34 PLN. With a retrospective analysis, based on historical usage, one could see that the optimal values for contracted capacity would vary between 72 kW and 90 kW, depends on the month, as presented in the Table 2. Knowing that, the customer could benefit from lower bills, so the cost of the optimal contract would be 7930.49 PLN, which is 26.5% less than actual cost. Once again, we used multiple output forecast strategy with ANN to estimate maximum load for each hour and these values were used further as the input to the genetic algorithm the forecast for the optimal contract level so the total cost is minimized. As the result the forecasted capacity was between 73 kW and 89 kW, depends on the month. There were instances where the usage would exceed the contracted capacity, e.g. 1 times in November and December. Finally, the total cost of optimal contract predicted by the network and optimized by genetic algorithm was 8068.66 PLN. In comparison to the actual cost, the benefit of the customer is also material, similarly to the previous customer, and amounts to 2720.68 PLN (10789.34 – 8068.66) which is 25.2% of the actual bills.

**Table 2.** Multiple output forecast strategy with Q100 for C22b tariff user.

| Actual values | | | | Optimal values based on historical usage | | | Optimal values based on predicted usage | | |
|---|---|---|---|---|---|---|---|---|---|
| Month | Actual contract [kW] | Actual cost [PLN] | Above actual contract | Opt contract capacity [kW] | Opt contract cost [PLN] | Above Opt contract | Opt contract capacity pred [kW] | Opt cost capacity pred [kW] | Above opt capacity pred |
| Mar | 80 | 1402.71 | 62 | 86 | 860.27 | 1 | 88 | 880 | 0 |
| Apr | 80 | 800 | 0 | 78 | 786.63 | 1 | 85 | 850 | 0 |
| May | 80 | 800 | 0 | 72 | 722.82 | 1 | 77 | 770 | 0 |
| Jun | 80 | 800 | 0 | 72 | 724.28 | 1 | 73 | 730 | 0 |
| Jul | 80 | 800 | 0 | 73 | 737.81 | 2 | 74 | 740 | 0 |
| Aug | 80 | 800 | 0 | 74 | 740 | 0 | 74 | 740 | 0 |
| Sep | 80 | 800 | 0 | 76 | 760 | 0 | 76 | 760 | 0 |
| Oct | 80 | 800 | 0 | 78 | 780 | 0 | 78 | 780 | 0 |
| Nov | 80 | 1547.07 | 58 | 87 | 874.71 | 1 | 87 | 874.71 | 1 |
| Dec | 80 | 2239.55 | 266 | 90 | 943.96 | 1 | 89 | 943.96 | 1 |
| Total | | 10789.34 | | | 7930.48 | | | 8086.66 | |

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## 5 Conclusion

In this paper two stage approach is proposed to determine appropriate contract capacity amount that minimize financial losses in case of exceeding the amount of capacity defined in the contract. The LSTM neural network model was developed. The first stage was to forecast hourly capacity values as the basis for determining the monthly maximum capacity required. These maximum values were used to determine the optimal monthly capacity values at the second stage, so the values were provided as the input to the genetic algorithm in order to establish such monthly contract capacity level that would help the user to avoid charges for exceeding the contracted level.

As shown through the experiments, the application of multiple output forecast artificial neural network model and genetic algorithm for load optimization delivers significant benefits to the commercial customers. In comparison to the actual costs, the benefit for the customers, due to optimization, is material. Specifically, the benefit for the C22a customer is 15.5% of the actual bills while for the C22b customer it is 25.2%.

As a future work, we would continue the research towards fitting the models so these could potentially better deal with seasonality of the demand on the customers end. Although this research deals with Polish tariffs, we believe it can be applied to other electricity customers in capacity cost decision making.

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