Intelligent Analysis of Data Streams

Viera Rozinajová[1][0000-0003-1302-6261], Anna Bou Ezzeddine[1][0000-0002-3341-6059], Gabriela Grmanová[1][0000-0001-9024-8584], Petra Vrablecová[1][0000-0003-0365-3798], Miriama Pomffyová[2][0000-0002-0411-3809]

[1]Kempelen Institute of Intelligent Technologies
Mlynské Nivy 5, 811 09 Bratislava, Slovakia
energo@kinit.sk

[2]Faculty of Informatics and Information Technologies
Slovak University of Technology in Bratislava
Ilkovičova 2, 842 16 Bratislava 4, Slovakia
miriama.pomffyova@stuba.sk

Abstract. The huge amount of data generated on a daily basis in many areas of our lives predetermines data science to be one of the most significant current IT research areas. Thanks to the recent technological trends, such as internet of things (IoT), the data streams constitute a majority of currently created data. This chapter aims to provide one possible view on the recent trends in stream mining. Our focus is on two frequent data mining tasks – namely the prediction and the optimization. We have several years of experience in predictive modeling and we would like to offer here a summarization of the selected outcomes of our research work. The domain in which we have verified our methods, is the power engineering area. Due to population growth and technological advancement, there has been a huge increase of global energy demand in recent years.

The ultimate goal is to manage the energy supply in the most efficient way. To propose smart solutions, the first step is to have a clear idea about its future consumption and production. Then we can proceed to efficient control of the smart grid, by involving recent trends in optimization and utilizing machine learning approaches. Hence the second part of the chapter is devoted to our endeavors in solving tasks of smart grid optimization. The common denominator of the described approaches is the effort to cover various types of knowledge entering these procedures.

Keywords: data analysis, big data, stream mining, time series, prediction, optimization.

1 Introduction

As we all know, the 21-st century can be characterized as a century of digital transformation. Paradigms such as *artificial intelligence (AI)*, *internet of things (IoT)*, *5G*, *high-performance computing* and *data analytics* play a crucial role – they represent emerging technologies, which will significantly change our lives. If we succeed to build the technological progress on these phenomena, respecting also ethical foundations, we will witness the formation of veritable *digital intelligence society*. It is based on several pillars – however, we are convinced, that the ability to acquire and utilize knowledge will be the key distinguishing factor of competitiveness. This fact also implies the transition of current economy to the knowledge-based economy.

We can consider the knowledge from several angles. From societal point of view its engagement in decision-making process is a significant determinant of economic growth. Our interest is much narrower: we explore the emplacement of various types of knowledge in the processes and procedures of analyzing and processing data. In order to streamline these processes, technical expertise about methods and algorithms is required and knowledge about an exploding number of analytic approaches is very useful. A big deal of this expertise is a tacit knowledge of the experts. However, the identification and subsequent explicit representation of this type of knowledge would be of great value. This paper presents one view on a given topic. It deals with knowledge, used in the process of solving specific tasks of data mining. Our endeavor is to cover various types of knowledge to provide preliminary view on its possible later formalization and representation. The most important types of knowledge that are necessary to successfully solve data analysis tasks are [54]:

- *existing different techniques that can be applied in the data analysis process*,
- *metadata on the input dataset*, and
- *predictive models, or other types of models.*

The whole process is supported by the *domain knowledge* of the given area.

As mentioned earlier, the goal of this chapter is to provide an insight into data scientist´s know-how, whereby we deal with expert knowledge, as well as with domain knowledge.

The huge amounts of data are generated daily in almost every area of our life. It is clear, that the value which is hidden in these data can be discovered only if these data are properly analyzed. Our focus is on processing data streams, as due to the contemporary technologies such as IoT, the stream data constitute a majority of currently generated data. From among many data analysis tasks, we concentrate on predictive modeling and optimization. Our group has explored relatively many approaches to solving prediction task. Basically, two approaches to analyze data are used: statistical methods and recently very popular machine learning techniques. We have experience with both types, and we aim to share our experience with them and provide the outlook on the whole area of stream mining, stream forecasting and optimization. In our research, we have verified the proposed methods in the domain of power engineering. Within the scope of this chapter we have selected use cases from the domain of power engineering – also to make feasible to discuss the incorporation of domain knowledge into the model creation, e.g., to include the given constraints into the solution.

In power engineering domain, the traditional grid is changing. It is no more centralized network, where all power customers take energy from the main source. Rather it becomes a distributed network, where the customers will not be just consumers anymore, but they will become prosumers, who consume and produce the energy from renewable energy sources. To effectively use the generated energy, it is important to predict its consumption and production as precisely as possible. Based on these predictions we can then manage the operation of the grid. Here the optimization methods have their firm place. Our goal is therefore to continue the research in the field of optimization methods to offer intelligent smart grid solutions and thus to contribute to an important problem of energy supply.

This chapter is organized as follows: section 2 provides a brief introduction to stream mining in general, in section 3 approaches to stream forecasting are reviewed and our research in this area is mentioned, i.e., our activities towards prediction of energy consumption and production. Based on these outcomes we move on to an important problem of contemporary smart grid – an optimization of its operation. We introduce our efforts in smart grid optimization in section 4 and conclude the chapter in section 5.

2 Stream Mining

The need for efficient processing of large volumes of data resulted in emergence of the stream mining research field. The data streams have similar properties as *big data*: volume, velocity, and variety. Since the data in the stream flow constantly, their volume is essentially infinite. The individual values can come in regular intervals at various speed in one or more simultaneous streams comprising time series. The data can come from diverse sources and change their nature over time due to influence of miscellaneous factors.

Unlike traditional batch mining, stream mining has several restrictions and there are special requirements for data stream processing:

- *accuracy* of stream mining method should not differ significantly from the batch mining method,
- *timeliness* of the stream mining method results should correspond to the interval of data arrival and the results should be provided early enough for decision-making,
- *adaptivity* should be a key part of the stream mining method to cope with the evolving data characteristics in dynamic environments.

Stream Processing and Concept Drift Problem. The learning algorithms in general can be divided into categories based on the amount of data present in the learning process (see Fig. 1). While in offline learning mode a whole training set is needed to create and deploy a model, in online learning mode the data are processed sequentially, and the model is continuously updated with the arriving data. The individual levels of learning differ in the ability to access past data (partial memory) and the frequency of model updates, i.e., batch-by-batch processing in incremental algorithms vs. one-by-one processing in online algorithms [28].

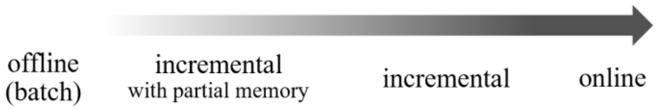

Fig. 1. Types of learning algorithms according to [28].

The incremental and online algorithms can address the last requirement for the stream mining methods – adaptivity, which is closely related to the *concept drift* problem. This problem manifests mainly in the predictive data mining tasks but can be also observed in the results of descriptive tasks if repeated successively over time. "Concept drift means that the statistical properties of the target variable, which the model is trying to predict, change over time in unforeseen ways" [38]. There exist several types of drifts, e.g., abrupt (sudden), gradual, incremental, recurring, etc. [28, 38, 51]. Unfortunately, most of these types are not yet thoroughly formally defined and examined and more studies on their nature are required [35]. Moreover, outliers and noise in data can be easily mistaken for concept drift.

The goal of *adaptive* incremental or online algorithms is to adapt to the changing data stream. Depending on the inclusion of an explicit concept drift detector in the algorithms we differentiate *active* (or informed) and *passive* (or blind) approaches [19, 28, 38]. Ramírez-Gallego et al. [51] identified four main approaches to efficiently tackle the drifting streams: an active approach via *concept drift detectors* and three passive approaches – *sliding widows*, *online learners*, and *ensemble learners*. The passive approaches adapt implicitly over time by continuous learning. The active approaches detect the drift in data stream and react to it only if detected. Lu et al. [38] described three main groups of drift reaction methods in active approaches: *simple retraining* (a new model is retrained and replaces the obsolete model), *ensemble retraining* (a new model is retrained and added to the ensemble of models) and *model adjusting* (a part of the existing model is replaced).

The concept drift problem has been recognized in increasing number of areas, especially in big data community [38]. Lately, several extensive survey papers concerned with this problem [19, 28, 38] or included it as a related issue [35, 51].

3 Stream Forecasting

As mentioned earlier, the stream mining area covers both predictive and descriptive data mining tasks. In our research, we aimed at prediction, i.e. stream forecasting in one particular application domain – power engineering. Prediction of power consumption and production is a typical real-world example of learning in a dynamic and evolving environment [19].

The process of stream forecasting consists of three steps [28]: *predict, diagnose and update* (see Fig. 2). The last two steps are optional since they are part of active adaptive approaches only. These three steps repeat continuously as new samples/batches from the stream arrive.

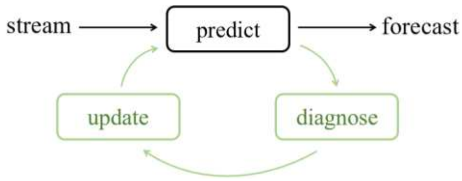

Fig. 2. The stream forecasting process [28].

Open problems. The most emphasized open problem in the literature is the transformation and optimization of existing offline methods to online or incremental methods [24, 35]. The demand for this kind of methods originate from the ever-growing production of data, i.e., the big data phenomenon, but also from the hardware miniaturization trend that calls for energy efficient methods, which can work with a limited memory space [24]. For successful utilization of offline methods in stream forecasting, the methods require adjustments to achieve *lower computational complexity* and *ability to adapt to concept drifts*.

A significant drop in time and memory complexity can be achieved by removal of redundant data by their approximation [46] and creation of hybrid approaches that combine the prediction methods with methods for transformation of raw time series data to more efficient representations [24]. The complexity reduction and online data pre-processing is suggested to be a mandatory step of the stream mining process [51].

The complexity reduction issue also relates to over-parametrization of mining methods and the need for parameter free data mining approaches [24]. Automated or semi-automated parameter tuning can alleviate this problem, e.g., by utilization of optimization algorithms. This problem is also mentioned in the context of ensemble learning where it is referred to as a problem of self-tuning ensembles [35].

The other way to more efficient mining approaches, is development of methods that are dynamically adaptive to varying nature of data streams, i.e., the concept drift [24]. The concept drift problem requires research of incremental methods that can continuously learn but also forget obsolete knowledge [46]. There is also a lack of research on effective integration of concept drift handling techniques with machine learning methods [38]. The research on concept drift methods is heavily affected by missing benchmarking tools, such as uniform datasets used across papers. The datasets should come from different real-world applications [24, 35, 38] or synthetic data generators [46] and cover various types of concept drifts.

3.1 Power Demand Forecasting

Traditional static time series prediction methods learn the model from the batch of data and are subsequently used without the need to persistently relearn the model. The prediction methods can be divided into two main groups [44]:

1. *statistical*/stochastic methods and
2. *artificial intelligence*/data mining/machine learning methods.

These are often combined into *ensemble models* to exploit the different qualities of multiple methods or to amplify the quality of a single method.

Statistical methods. In general, statistical approaches model future values based on historical data. Since the future value is not exactly determined by past values, the series is not deterministic, and we speak about stochastic process.

The most popular statistical approach for time series prediction and popular power demand forecasting method is called *Box-Jenkins methodology* [5] and its autoregressive (AR) and moving average (MA) models and their combinations, such as ARMA, ARIMA [2], ARMAX [36], ARIMAX [71], SARIMA or SARIMAX.

Another popular statistic method for time series analysis and prediction is *exponential smoothing* [9]. Unlike AR and MA models that consider only several past values given by the order of the model and weight them equally, exponential smoothing considers all past values from the beginning and weights them by smoothing factors that decay exponentially. This results to the simple model, where older values have smaller weights than more recent ones. When the time series contains a trend, recursive application of an exponential filter twice or three times results to double and triple exponential smoothing, respectively. Exponential smoothing was successfully used to predict electricity load consumption [61, 62]. In our research, we have extended the double exponential smoothing with concept drift detector based on the domain knowledge – the fact that the daily error of a good power demand forecast should not be higher than 5%. We found out that this incremental approach can significantly save computing resources and provide precise results even when concept drift occurs [64, 65].

Seasonal decomposition of time series by LOESS (STL) [13] decomposes time series into trend, seasonal and remaining components. The decomposition is based on LOESS – a nonparametric regression technique that uses local weighted regression to fit a smooth curve through points in a sequence. STL is robust to outliers. STL was also used to predict monthly electricity consumption [59].

The most utilized family of statistical models used for making continuous predictions is known as *regression analysis*. The dependent variable is predicted based on independent variables. They are known as regressors, exogenous or explanatory variables. In time series analysis, time and calendar variables, such as month, day of a week or hour of a day, are used instead of historical values. Regression models were used to make predictions for power load consumption [11, 68].

AI methods. The second family of models for time series analysis and prediction solve a regression task by advanced methods of artificial intelligence. The values are modeled based on calendar, time, selected historical data and other exogenous variables.

Artificial neural networks do not require to determine the type of function between input and output in advance. The output predicting function is learned in the form of patterns based on historical data time/calendar variables and/or exogenous variables. Neural networks are very suitable for modeling nonlinearities in data and have a theoretically proven ability to approximate any complex function with arbitrarily chosen accuracy. They have been used extensively to predict electricity consumption since the late 1980s [41]. Their great advantage is that they can naturally model the influence of various exogenous variables on sampling values. On the contrary, the disadvantage is that they belong to so-called black-box models, where the predictions cannot be explained. The most used neural networks are multilayer forward neural networks [34], recurrent neural networks [16] or, recently, deep neural networks [18].

Support vector regression (SVR) [21] is a regression version of the well-known support vector machines (SVM). SVR searches for an appropriate line or hyperplane (in higher dimensions) fitting the data within decision boundaries around the hyperplane in distance given by the tolerable error. Slack variables are usually added into the model to allow approximation in the case that all data cannot lie within the decision boundaries. Similar to SVM, in the non-linear case, kernel functions are used to transform the data into higher dimensional feature space where data exhibit linearity, without increasing the computational cost. SVR were successfully used for electricity load forecasting [40]. For stream forecasting of power demand, we have extensively studied the online variant of SVR with one-by-one processing and forgetting ability [67].

Regression trees are predictive models based on the decision trees addressing the classification problems. However, the output of regression tree is a continuous value. Usually, it is calculated as an average value of items that ended up in the final leaf of the tree during the tree training. To achieve better prediction accuracy, many strategies how to use multiple regression tree predictors were formed. Regression trees were used for power load forecasting in [33].

The advantages and disadvantages of both statistical and AI methods are summarized in Table 1.

Table 1. Pros and cons of power demand forecasting methods [66].

	statistical	*artificial intelligence*
pros	• easy interpretability • few parameters to estimate • better univariate models	• minimum statistical or domain knowledge required • ability to model also non-linear relationships between power demand and exogenous variables (e.g., weather) • better multivariate models
cons	• ability to model only linear relationships • low accuracy in longer term • statistical and domain knowledge required	• difficult interpretability • over-parametrization • heavy computation without optimization

Ensemble models. The basic idea of ensemble learning is to combine the results of simpler (weak) classifiers or predictors, called base models, to achieve better results. Combined weak methods should be independent of each other and their accuracy should be better than the accuracy of a random model. The three basic approaches are:

- *Bagging* [7] achieves the diversity of basic models by using a bootstrap approach to select a subset of the data on which the model is learned. Random forests [8] represent a certain generalization of bagging. In the process of creating trees, only a randomly selected subset of attributes is used in each division (branching) of the tree.
- *Boosting* approach [53] builds a set of methods sequentially, starting with one model and gradually adding another so that a new model is created based on the errors of the previous base models. Gradient boosting [26, 27], which can be used to optimize any differentiable loss function, is a very popular approach used for regression.
- *Stacking*, unlike previous approaches, where the same types of basic models (e.g., regression trees) are trained, combines the predictions of two or more different basic models (e.g., a regression tree and a support vector regression).

Ben Taieb and Hyndman [60] used gradient boosting to predict electricity consumption. They created semi-parametric additive models and used gradient boosting to estimate the parameters of these models. Papadopoulos and Karakatsanis [48] compared random forests and gradient boosting regression trees with seasonal versions of the ARIMA and ARIMAX prediction models. Ruiz-Abellón et al. [52] compared 4 ensemble methods – bagging, random forest, gradient boosting and so-called condition trees to predict the next 48 samples. The results demonstrated the effectiveness of ensemble learning approaches, especially random forests and gradient boosting. The stacking approach, i.e. combining heterogeneous models to obtain more accurate predictions, has been applied in [10, 20, 47]. We have also proposed an incremental ensemble learning method based on stacking. In the design, we employed the domain knowledge that comprises the knowledge about strong seasonality of the data and the need to consider sudden or gradual concept drifts. The ensemble approach was chosen for its ability to quickly adapt to changes in the distribution of predicted variable and its potential to be more accurate than a single method. Predictions of particular base models can be computed in parallel in order to reduce computation time and to scale up to incoming amount of data which makes the proposed ensemble suitable for big data streams. We selected a wide spectrum of base models and proposed two weighting schemes for combining the base models' predictions – a scheme based on median error of the base models [32] and utilization of biologically inspired optimization algorithms for weighting [4, 31]. We focused on studying the effects of seasonality and concept drifts.

3.2 Power Production Forecasting

The task of dynamic prediction of electricity production from renewable energy sources (RES) is equally important as power demand forecasting and employs similar methods. The production can be unstable, resulting in large actuations of energy, which might cause instability of the grid. Therefore, it is necessary to predict it so that grid operators can plan power generation or effectively regulate the grid to ensure its stability. Photovoltaic (PV) panels obtain energy from solar radiation. Unlike PV, wind energy does not have daily seasonal patterns, instead it depends on local meteorological effects, thermal exchange between ground and atmosphere and general changes in weather patterns. There are three main approaches to prediction of RES energy [1, 55, 69]:

- *Statistical methods.* Statistical approaches use only data from the past, which contains information about weather and production of photovoltaic power plant. For a short term, up to 36 hours, statistical methods can prove to be a bit accurate.
- *Physical methods.* Physical approaches use weather forecasts and technical parameters of photovoltaic power plants or wind turbines, which are necessary for calculation of approximate electricity production.
- *Ensemble methods.* Hybrid approaches combine previous approaches to the ensembles to improve prediction. Ensemble or hybrid methods use a combination of different statistical and physical methods with the goal of improving the accuracy.

Artificial intelligence methods are powerful in predicting photovoltaic power production, but their accuracy is highly dependent on their hyperparameter setting. The hyperparameter setting can be done in various ways, either manually or by using algorithms capable of finding and evaluating different hyperparameter settings, such as nature-inspired algorithms. In our most recent research, we proposed the utilization of firefly algorithm to optimize hyperparameters of a SVR model for PV production forecasting [58].

4 Optimization

After a detailed research of forecasting methods, we explored other possibilities of using prediction to increase the efficiency of processes. One of the possible ways to use prediction is in optimization problem, where based on predicted attributes, it is possible to create a plan for a few days ahead. For example, based on the prediction of electricity consumption and production, we will create a plan for the use of batteries to store energy produced by photovoltaics using optimization methods.

4.1 Optimization Process and Open Issues

The aim of the optimization process is to find the best fit result from a set of available feasible solutions that met the conditions of the set model. It is very important to determine the correct model of the problem to be optimized based on domain knowledge. It is necessary to create a formula that describes the real world as much as possible. By setting the values of decision variables, it is possible to maximize or minimize objective functions. Optimization methods are used to solve various types of problems, such as linear, nonlinear, undifferentiated, or dynamic problems. Williamson & Shmoys [72] describe theory and taxonomy of optimization.

The optimization with many objective functions to minimize or maximize is called multi-objective optimization. It is very important to identify objective functions and their constraints, set the limits and conditions correctly [15]. The main problem of multi-objective optimization is that if there is an optimal solution for one function, it is uncertain that it will be optimal for other functions as well. It sets this problem especially when the goals of the objective functions are contradictory. Therefore, the task is to find solutions that are optimal or nearly optimal for each function at once [76]. Pareto optimality represents a solution that is a compromise between all suitable solutions. The problem of pareto optimality is also dealt with in other works, which describe, e.g., the conditions of optimality and the division of the set of solutions [15, 22, 25].

Several open issues need to be addressed when designing a solution for multi-objective optimization. There are several multi-objective optimization review articles that describe currently open issues and challenges [3, 14, 39].

The current research challenges that many authors view from some aspects are:

- *Real time processing and dynamics*. Multi-objective optimization is computationally demanding and therefore no real-time solution is defined for this type of optimization. It is also difficult to include problem dynamics into the modelling and real-time optimization process.
- *Hierarchy between objective functions.* In two-level problems, when one of the objective functions is subordinate to another, its evaluation is used as a limit in the superior, the computational complexity increases.
- *High dimensionality.* With many objective functions, it is difficult to evaluate the principles of the dominance of found solutions, and therefore most solutions can be evaluated as equally successful.
- *Experimental verification*. Test objective functions are used to evaluate the success of optimization algorithms, but they do not necessarily cover real-world situations. Also, with an increasing number of objective functions the calculation time for evaluation of the objective functions increases [39, 63].
- *Visualization*. The result of evolutionary algorithms for multi-objective optimization is a Pareto-optimal set which contains optimal solutions. To select a suitable solution, it is possible to visualize the results, but with an increasing number of objective functions, it is not trivial.

4.2 Optimization Methods

There are currently several approaches to address optimization. Approaches can be divided into *analytical* (mathematical or exact), *numerical* (approximation or metaheuristics) and their combinations (*hybrid*) [12, 63]. Depending on the complexity of the modelled optimization problem, it is necessary to decide which method to use. If the level of complexity is low enough, it is possible to use analytic methods that guarantee the optimum solution. However, due to the nature of large data and multiple objective functions and with the increasing complexity of the problem, it may be better to use metaheuristics.

Metaheuristics and their exploration and extraction mechanisms provide a reasonably good solution at a reasonably appropriate time [17, 29]. An example of metaheuristic approaches are biologically inspired methods, for example, neural networks, which were created based on the functionality of the human brain, or genetic algorithms, which copy the behavior of evolution in nature. Biologically inspired methods can be divided into three groups: *swarm intelligence*, *evolution-based* and *ecology inspired algorithms*. Bou Ezzeddine et al. [4] described these groups of biologically inspired methods in more detail. These algorithms have been used, for example, in [6], when the mathematical model have been proposed with the aim to optimally manage the smart polygeneration microgrid to minimize daily operational costs and carbon dioxide emission. In the work [45], authors formulated objective functions representing charging and discharging costs, losses, and voltage profile.

The choice of optimization algorithm type depends also on the end user's involvement in the optimization process. In terms of user preferences, according to many authors [15, 22, 75], the methods are divided into four main groups:

- *Methods without knowledge of preferences*. User preferences are not considered, and we want to achieve Pareto's optimal solution, which means a generated neutral compromise. This approach is mainly used when the end-user preferences are not known, and he does not participate in the simulation process.
- *Priori methods*. User preferences are considered and therefore end-user requirements are included in the simulation process. This user information is used for subsequent scalarization of features.
- *Posteriori methods*. The output of the algorithm is a set of solutions from which the end-user can choose the solution that seems to be the best one, in his opinion. Its requirements may be included in the process, but there is no need for its preferences to be included in the input of the algorithms.
- *Interactive methods*. The end user intervenes in the process of selecting solutions for searching in the algorithm solution space so that the selection is directed to its preferred solution. The iteration process is repeated until the user decides to end it.

4.3 Evaluation of Optimization Methods

We can divide the evaluation of the optimization methods based on whether we evaluate *the success of the optimization algorithm* or *the achieved optimization results* [22, 37, 63, 74]. In terms of the success of the optimization algorithm, the result of the multi-objective problems (MOP) should be non-dominated and as close as possible to the Pareto optimal front, just like convergence to the global optimum in single-objective optimization [22, 73]. The most important part of optimization is evaluation of performance of different types of algorithms [14, 37]. The test functions, such as bi-objective Zitzler-Deb-Thiele suite (ZDT) and scalable Deb-Thiele-Lau-mans-Zitzler suite, are used for performance evaluation of multi-objective capabilities in approximating the Pareto front [22]. These function tests non-convexity, multi-modality and non-uniformity of the search space, and discontinuity. Discontinuity of solution usually cause difficulties in solving multi-objective evolutionary algorithms. If the algorithm can solve such test functions, there is a great possibility that it will be able to solve multi-objective problems of the real world.

In terms of evaluating the results of optimization, the most commonly used way to evaluate the success of optimization is to express the values of objective functions. For example, in the domain of power engineering in the process of evaluating the results of optimization, the following indicators can be evaluated: the amount of energy consumed from the mains, the amount of energy consumed from the energy produced by photovoltaic cells, fluctuations and the connection of the curve of energy consumption from the main network, the total price of energy consumed from the mains.

If the stream processing requirements are met, it will be possible to create an online (stream) forecast and then create a real-time optimization plan. Some of the metaheuristic methods can provide multiple solutions, so the decision-maker will be able to choose a suitable solution in time.

4.4 Microgrid Optimization Problems

Microgrids must have a specific management strategy that operates distributed energy resources, trades energy with the main grid and manages the energy load [49, 77]. A hierarchical control structure is used, which is formed of three layers controls. Each layer is used to manage specific actions of the microgrid systems. The primary control layer focuses on real-time control of the microgrid. Its main task is to keep the local voltage and frequency at optimal levels, which is achieved using a technique called droop control [56]. The secondary control layer operates over periods of seconds up to minutes. It aims to compensate for larger deviations in voltage and frequency caused by changes in load or renewable energy production. The tertiary control layer usually operates in matters of hours or days. The main focus of this layer of control is the economic concerns and it manages trading with main grid. This level of control typically involves the collection of information on energy prices, weather forecasts, renewable energy production forecasts and energy load forecasts. Based on these forecasts, a plan for grid trading and generator management is created. This plan is mostly created with economical goal in mind, but it could be even more complex multi-objective one. The schedule can range usually around 24 hours.

We assume that the problems of the real world need to be modelled by several specific objective functions that can be optimized. Efficient management of energy consumption, electricity production and storage are a possibility to spend less money on electricity and produce a more accurate amount of energy. There are three main categories that can benefit from optimization in power engineering:

- *Microgrid planning/microgrid sizing.* We can determine the optimal architecture (i.e., the number and type of correct components) due to its expected size and environment with the aim to produce the expected amount of energy consumption.
- *Microgrid operation.* We can adjust the optimal amount of energy produced to the expected consumption and in order to achieve the lowest possible cost.
- *Microgrid control.* We can optimize models describing network status to increase network reliability (i.e., planning, implementation and monitoring of activities of electricity producers).

The application of domain knowledge in the process of prediction and optimization can have a positive impact on more efficient energy management. For example, in case we have knowledge of what kind of electricity consumption it is, we can determine the start-up time of the appliance or limit the amount of consumption when creating a recommendation for the end consumer. Several grid components and their integration are described by many authors [43, 49]. An example of grid components that we should consider when creating a model are:

- *electric appliances*:
  - fixed – we cannot manipulate the consumption, e.g., security system,
  - flexible – we can manipulate the consumption to optimize the smart grid, there are appliances whose consumption we can limit (e.g., air conditioning or lighting) and those whose consumption we can move (e.g., washing machine, dishwasher),
- *distributed energy resources* (DER):
  - controllable – we can turn off and on demand or set the power level (e.g., diesel generator),
  - uncontrollable – we cannot control power level, e.g., renewable energy sources (such as solar collectors and wind turbines),
- *devices useful for energy storage*, e.g., energy storage systems with batteries.

Based on the knowledge of the batteries used in the microgrid domain, we can more accurately create a plan for their use. The maximum and minimum battery charge limits are given by its capacity. To prolong battery life, it is possible to change the battery charge and discharge limits settings. Sufyan et al. [57] and Prodan et al. [50] state that battery life decreases with the number of charges and discharges. They define battery life as the number of full charges and discharges until its capacity drops to 80% of its original value. They also state that battery life is also affected by depth of discharge (DOD), which is the opposite of its state of charge (SOC). Weniger et al. [70] mention that in addition to the number of charges and discharges of the battery, its life is also affected by its state of charge. The authors keep SOC batteries in the range of 20% to 80% of its original capacity. To charge the battery to more than 80%, it is necessary to maintain a constant high voltage, which is harmful to the battery in the long run. The limit for batteries is also the maximum amount of battery discharge per hour (e.g., 5 kWh). The worst case of battery use is frequent full discharge cycles. It is optimal to limit the battery charge from 80% to 20% of the original capacity.

Objective functions are identified based on similar domain knowledge. When planning microgrids, the reliability criterion is evaluated, which is usually measured using parameters such as the ratio of *forced outage rates* (FOR), *expected energy not served* (EENS) or *loss of load probability (expectation)* (LOLP (E)) [30]. For example, the LOLP (E) is a criterion that measures how much time (hours) a given energy source will not meet the requirements for supplied energy (i.e., some customers will not receive energy/will be disconnected) during the total number of n hours (1) [23].

$$LOLP = \frac{\sum_{i=0}^{n} Deficit\ load\ time}{n} * 100\% \tag{1}$$

The LOLP of the system can be used as a limitation of the objective function when the value of the LOLP should be lower than the allowable LOLP reliability index.

When optimizing the operation of the microgrid, the goal is to minimize the difference between the energy produced and the electricity consumed. In this case, economic dispatch is used in the short term, and unit commitment in the medium term. For example, in calculating the economic dispatch energy costs are minimized by determining the optimal generator power output, P_k, grid power P_{grid}, and energy storage state of charge SOC_r at each time step i, such objective function is used (2) [42].

$$\min \sum_{i=0}^{n} \left\{ \sum_{k=0}^{g} F(P_k)_i + F(P_{grid})_i \right\} + \sum_{r=0}^{s} F(SOC_r)_n \tag{2}$$

There are n time steps $i = 1,2,3,\ldots$, and g dispatchable generators and their cost $F(P_k)$. $F(P_{grid})$ is a time dependent price for either purchasing or selling power and $F(SOC_r)_n$ represents energy that remains stored in the s energy storage devices at the end of the forecast horizon. In determining this objective function, knowledge of the battery used to store electricity was utilized. Such inclusion in the objective function ensures that solutions which fully deplete the storage are not always preferred. By setting specific optimization goals, it is possible to determine many objective functions and their constrains.

5 Conclusion

The goal of this chapter was to provide a competent view on the recent trends in stream mining with special focus on its application in energy domain. Our team has several years of experience in research of predictive modeling – we have explored many approaches and performed a lot of experiments in searching for effective ways of forecasting power load consumption and production.

The first part of the chapter is therefore devoted to selected methods and techniques of stream forecasting. In our research, we payed a great deal of attention to ensemble learning – a composite model, integrating different individual models, aiming to reduce prediction errors. The potential of ensemble models is known for quite a long time; however, we found a challenge in improving some of its features. The main reason to use ensemble learning was its ability to quickly adapt to changes in the distribution of predicted variable. We proposed an incremental ensemble model for electricity load forecasting based on stacking strategy [32]. We applied biologically inspired algorithms for updating weights in the ensemble [4, 31]. Our interest was to improve the performance of ensemble learning in the presence of different types of concept drift that naturally occur in electricity load measurements. Besides the passively adapting ensemble model, we studied an incremental approach with active adaptation [64, 65] and later an online learning approach [67], which were oriented on effective utilization of computing resources within stream processing. Recently, we focused on application of biologically inspired algorithms on hyperparameter tuning of power production forecasting models [58].

The natural continuation of research in the power load domain is to find effective solutions of controlling the energy supply. Reliable consumption and production predictions are inevitable preconditions of planning process for the next periods. For example, we can schedule the effective usage of batteries to store energy produced by photovoltaics using optimization methods.

In the new concept of electrical network, the term microgrid is becoming very popular. It represents a localized group of electrical sources and loads, that normally operates within the central electrical network, but may also be able to disconnect and to function autonomously. There are several areas of microgrid design, where advanced optimization methods can improve the whole process: propose the optimal architecture (i.e. the number and type of correct components), plan microgrid operation (prepare the optimal amount of produced energy in order to supply expected necessary consumption), establish microgrid control (planning, implementation and monitoring of activities of electricity producers). These problems constitute the challenges for our future work.

Our work was closely associated with identification of knowledge, used in data analysis processes. We considered both types of knowledge – expert and the domain one. Appointing the relevant know-how of the given area is the first important step before its formalization and utilization. Then, the selection of possible relevant knowledge representations can take place. Among other topics, this will be the subject of our further exploration.

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