On Designing Data Models for Energy Feature Stores

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Abstract—The digitization of the energy infrastructure enables new, data driven, applications often supported by machine learning models. However, domain specific data transformations, preprocessing and management in modern data driven pipelines is yet to be addressed. In this paper we perform a first time study on data models, energy feature engineering and feature management solutions for developing ML-based energy applications. We first propose a taxonomy for designing data models suitable for energy applications, analyze feature engineering techniques able to transform the data model into features suitable for ML model training and finally also analyze available designs for feature stores. Using a short-term forecasting dataset, we show the benefits of designing richer data models and engineering the features on the performance of the resulting models. Finally, we benchmark three complementary feature management solutions, including an open-source feature store.

Index Terms—energy data model, feature store, energy feature management, machine learning

I. INTRODUCTION

With the transformation of the traditional power grid to the smart grid, the complexity of the system continues to evolve [1], especially with the penetration of smart meters (SM), energy management systems (EMS) and other intelligent electronic devices (IED) especially at the low voltage (LV) level of the grid. IEDs, together with EMS enable an innovative set of energy [2] and non-energy applications [3]. EMSes enable the control of various assets in homes or buildings with limited knowledge of grid status. Example energy applications are energy cost optimization, matching consumption with self-production from renewable energy sources (RES), or by trying to help distribution system operator (DSO) or aggregator to reach their predictive performance curves.

On the DSO side of the LV grid, the main challenges are represented by reliability and latency. In the case of controlling at substation level, the complete observability of the LV grid for that substation is of great importance. The data collected from all SMs in the grid of one substation would provide enough data to plan and minimize the possible congestion that may occur during the peak demand hours, or too high production of RESs that could lead to power quality issues (e.g. over-voltage).

In the case of medium voltage (MV) and high voltage (HV) network wide-area measurement systems (WAMS) already monitor and collect data. However, the data is collected only to provide observability and to efficiently handle the critical situations that might result in catastrophic events, in the worst case, power outages. Since reliability is the most important factor, the penetration of auxiliary services in the MV and HV grid is low. However, the data collected in the LV grid could be processed and used to enrich the collected data at MV and HV levels. The enriched data can be used to create a limited control loop that extends from the observability of the HV grid to control and make smaller adjustments as in the LV grid, all the way down to the prosumer.

While IEDs, WAMS and EMSes have been around for a long time, with their increased penetration, the amount of generated data is triggering the adoption on big data and machine learning techniques that are integrated in applications serving all segments of the grid [4], [5]. Data driven machine learning (ML) models are different than traditional statistical models in that they are able to automatically learn an underlying distribution. However, to achieve that, a well defined knowledge discovery process (KDP) needs to be followed [6]. The main steps of KDP consist of 1) data analysis, 2) data preparation (pre-processing), 3) model training and evaluation and 4) model deployment [7] as also represented in Figure 1. In the past, such process and the enabling tools were familiar only to a limited number of domain experts and the process involved intense manual effort. However, in the last five years, coordinated efforts have been taken by the private and public sectors to democratize AI and model development [8] to empower less specialized users.

The democratization process involves a division of labour and automation like approach applied to the KDP, as elaborated more in details in [7], where rather than a domain expert executing the step by step the process in Figure 1 from start to end, they only need to control the process at a few key steps. For instance, to develop a home energy consumption prediction model, the users need carefully select the relevant data, also referred to as data model, engineer the desired features, and configure the desired pipeline by selecting the ML methods to be applied and then selecting the best model to be deployed to production. Such automation is enabled by machine learning operations (MLOps) [7] and is being piloted in projects such as I-NERGY [9] and MATRYCS [10].

More recently, the authors in [10] proposed a “unification of machine learning features” in which a common/unified data preparation phase is best automated by feature stores

https://i-nergy.eu
https://matrycs.eu
Fig. 1: End-to-end infrastructure for machine learning model development and management.

(see phase 2 in Figure 1). Such approach further reduces the time spent on the most time-consuming phase of ML application development, benefiting data scientists, engineers, and stakeholders. While most of the MLOps automation steps are generic across domains, the ones concerned with data analysis and data preparation (pre-processing) have domain specifics and may significantly impact the model fairness and performance [11]. Assume aggregated home consumption is ingested from a smart meter and sent as is to train a ML algorithm. In such case, the model will learn the likely distribution of the values in the metering data and predict future energy consumption based on that, similar to the work in [12]. However, if additional weather data would also be used for training, the model would learn to associated lower energy consumption with sunny days and high temperatures, thus yielding superior performance. It is common practice in the literature to use such additional data. For instance, in [13] they estimated consumption using timestamp (month, hour, week of year, day of week, season), energy consumption, weather (condition, severity, temperature, humidity), energy price. In [14], the ML based estimation was done using timestamp, electricity contract type, energy consumption and city area.

In this paper we perform a first time study on data models, energy feature engineering and feature management solutions for developing ML-based energy applications. This is the first study that formalizes energy data modelling and shows feature importance and model performance trade-offs while also benchmarking feature management solutions. The contributions of this paper are:

- A taxonomy for designing data models suitable for energy applications and identification of relevant sources for the data categories in the taxonomy.
- Analysis of feature generation techniques and evaluation of their impact.
- An analysis of available solutions for realizing energy feature stores and the benchmarking of three solutions.

The rest of the paper is structured as follows. Section II elaborates on the proposed taxonomy for designing energy data models. Section III analyzes the feature generation techniques, Section IV discusses feature stores and available solutions while Section V details the evaluation and benchmarks. Finally, Section VI concludes the paper.

II. TAXONOMY FOR DATA MODEL DESIGN

In this section, we propose a taxonomy that identifies and structures various types of data related to energy applications. Based on this taxonomy, data models can be designed and implemented in database-like systems or feature storing systems for ML model training. The proposed taxonomy is depicted in Figure 2 and distinguishes three large categories: domain specific, contextual and behavioural.

A. Domain specific

Domain-specific features are measurements of energy consumption and production collected by IEDs installed at the various points of the energy grid. Additionally, information associated with energy-related appliances, such as the type of heating (i.e., heat pump, gas furnace, electric fireplace), can be presented in meta-data. In Figure 2 we identify PV power plant generation, electric vehicles (EVs), wind power generation, and household consumption. Power plants data include battery/super-capacitor capacity, voltage, current, power, and energy measurements and can be found in at least two publicly available datasets as listed in Table I. These datasets may also include metadata such as plant id, source key, geographical location, and measurements that fall under the contextual features group, such as air temperature. Wind power generation datasets contain the generated power and sometimes electrical capacity.

With a recent spike in the popularity of EVs, power grids need to be designed/improved accordingly because of their significant energy capacity and power draw. In the third column of Table I, we listed good quality publicly accessible datasets related to EVs. The datasets consider, for instance, battery capacity, charge rate, and discharge rate.

For household measurements, consumption may be measured by a single or several smart meters, thus being aggregated or per (set of) appliances. Depending on the dataset, they contain active, reactive, and apparent power, current, phase, and voltage. In some cases, meta-data about the geolocation, orientation, or size of the house may also be present. There are a number of good quality publicly accessible datasets, as can be seen from the fourth column of Table I.

B. Contextual features

We refer to contextual features as measured data that is not directly collected by measuring device(s), however such data [39] may be critical in developing better energy consumption or production estimates. In Figure 2 we identify 1) weather data such as wind speed/direction, temperature, relative humidity, pressure, cloud coverage and visibility, 2)
building properties such as type of insulation, year of building, type of property, orientation, area density and 3) time related features such as part of the day and daytime duration.

Weather datasets, such as the ones listed in the fifth column of Table I, usually provide numbers related to temperature and precipitation. Some also provide more climate elements like fog and hail, wind speed, humidity, pressure and sunshine/solar data. They also all provide the geographical location and the time period of measurement.

C. Behavioral features

Behavioral features refer to aspects related to people’s behavior such as work schedule, age, wealth class and hygiene habits as per Figure 2. Studies [20], [25], [27] show that electricity consumption is influenced by the behavior of the inhabitants. These are, for instance, personal hygiene, person’s age, person’s origins, work habits, cooking habits, social activities [20], and wealth class [25]. People of different ages have diverse electricity consumption patterns because of the difference in sleep habits and lifestyles in general. Social activities such as holidays, near-holidays, weekdays, and weekends also make a difference in the electricity consumption in homes, offices, and other buildings. Wealth class also influences electricity consumption because it impacts the lifestyle. If we are talking about a home, personal hygiene also has a major impact. Showering or bathing can take a considerable amount of warm water, depending on the showering frequency, shower duration, and how much water the shower head pours each minute. Besides that, we have to consider electrical devices such as a fan, hairdryer, or infrared heater.

Gender of the inhabitants also plays a role as men and women have different preferences when it comes to air temperature, water temperature [27] and daily routines.

While such data is useful for estimating and optimizing energy consumption, it raises ethical and privacy concerns. To some extent, such data can be collected through questionnaires, studies, or simulations to describe the behavioral specifics of users, groups, or communities.

III. Feature Generation Techniques

The data model designed for ML model training based on features from the taxonomy proposed in Section II typically consists of a mix of raw and engineered features as conceptually illustrated in the upper part of Figure 3. Feature
TABLE I: Datasets/studies for the feature taxonomy.

| PVs       | EVs       | Wind        | Household | Contextual features | Building | Behavioral features |
|-----------|-----------|-------------|-----------|---------------------|----------|---------------------|
| UKPN [15] | V2G [16]  | SandovalGER | [17]      | UKPN [15]           | HUE [19] | Social [20]         |
| Kannal [21]| emobpy [22]| LafazGER [23]|           | KannalIN [21]       |          | Wealth [25]         |
|           |           |             |           | SandovalGER [17]    |          | Gender [27]         |
|           |           |             |           | FIRED [24]          |          |                     |
|           |           |             |           | UK-DALE [26]        |          |                     |
|           |           |             |           | REFT [28]           |          |                     |
|           |           |             |           | ECO [29]            |          |                     |
|           |           |             |           | REDD [31]           |          |                     |
|           |           |             |           | iAWE [33]           |          |                     |
|           |           |             |           | COMBED [35]         |          |                     |
|           |           |             |           | HUE [37]            |          |                     |
|           |           |             |           | HVAC [38]           |          |                     |

engineering typically requires domain knowledge, experience and experimentation tends to be time consuming. New features can be produced by transforming the raw domain specific, behavioral and/or contextual data through linear or non-linear interaction, such as summation, subtraction and absolute value, statistical processing, i.e. by min, max, avg, moment computation, etc., dimensional reduction or expansion techniques as well as through feature interaction (cross-feature), an interaction of one feature and its historical values, or a combination of multiple interactions.

A. Statistical techniques

The most intuitive way to start building features from raw energy time series signals is to search for their statistical properties. Many researchers, such as [40], [41], suggest using statistical features to improve pattern recognition in time series. The most straightforward examples are computing summaries such as max, min, mean, standard deviation, variance, median, percentiles, etc. Tools, such as TSFresh [42], offer an abundance of statistical feature extraction options that can help automate the process of generating features for storing and model development. Recently, with the increased performance and popularity of deep learning algorithms, statistical features are less popular for building machine learning models, but are still very useful for dataset analysis and insight.

Statistical based features can be used for solving various problems in the energy domain. For example [43], [44] used these features to forecast energy usage in smart grids and residential area, respectively. Another example of using statistical based features is to detect appliances in Non Intrusive Load Monitoring (NILM) problem [45], while [46] proposed the use of statistical features for power consumption anomaly detection.

B. Dimensionality reduction techniques

In general, machine learning approaches provide better results when more, possibly independent features that, which are directly or indirectly related to a task, are added. These can expose previously unknown correlations or patterns to learn from, leading to better overall performance. However, increasing the number of input features can also increase computational complexity, also known as the “curse of dimensionality” [47]. Computational complexity then slows down the inference process [48].

To balance the performance/complexity trade-offs, dimensionality reduction techniques help reduce the number of input features while keeping as much variation as possible. These techniques are concerned with finding a smaller set of new variables, where each can combine the raw data. Some of the common dimensionality reduction techniques are Principal Component Analysis (PCA) [49], t-distributed Stochastic Neighbor Embedding (t-SNE) [50], Locality Preserving Projections (LPP) [51], and autoencoders (AEs) [52] in case of deep neural networks (DNNs). While LPP does not have an official implementation, both PCA and t-SNE are part of the scikit-learn python library [53]. AEs can be constructed using open-source libraries such as pytorch [54] or tensorflow/keras [55].

Dimensionality reduction techniques are widely used in energy domain for solving different set of problems. PCA is one of the most used techniques and has been utilised in forecasting of energy production [56], [57], energy consumption estimation [58], and NILM disaggregation and appliance classification [59], [60]. Although other presented methods are usually utilized for visualization of high dimensional data, some researchers proposed t-SNE as a dimensionality reduction method for NILM [61]. The DNN AE aproach was proposed by [62] to reduce the dimension of input data for later energy production forecast.

C. Dimensionality expansion techniques

Although dimensionality reduction techniques strive towards avoiding the curse of dimensionality, recently a trend is occurring to actually expand the dimensions of time series (TS) data. With the significant breakthroughs in image recognition [63] and image object detection [64] in the last decade, Wang et al. [65] proposed to use these algorithms to
solve TS classification problems, but first the TS traces had to be transformed into an image-like format. They proposed two new image-like representations of TS data in Gramian Angular Fields (GAF) and Markov Transition Field (MTF), which are now all part of the open-source library pyts [66]. In the same paper they showed that using image recognition deep learning algorithms on transformed TS data improved the classification results. Before Wang et al., Silva et al. [67] proposed a different TS representation to solve a TS classification problem called Recurrence Plots (RP) [68]. The idea of expanding TS dimensions is to incorporate additional information into the TS representation. Although in a different way, both GAF and RP calculate the temporal correlation between points within a time series, while a MTF represents a field of transition probabilities for a TS trace. All three transformations produce a square image representation of the input time series. Recently, another high dimensionality expansion technique was proposed, where subsections of TS were transformed into GAF and stacked together into a video-like format [69].

In energy domain, presented transformations are most commonly considered, but not limited to, for solving classification problems, such as device detection in Non Intrusive Load Monitoring (NILM). The usefulness of GAF transformation was shown by [69]–[71] where they selected GAF to distinguish between appliance types in NILM. Similar was done by [72], [73] only that they proposed a disaggregation method using GAF and subsequently determining whether an appliance is turned ON or OFF. An example of using RP for NILM device classification was shown by [74]. Though it is not strictly dimensionality expansion technique, [75] proposed a weighted pixelated image representation of the voltage–current trajectory (VI) to detect different types of appliances in the dataset. Alternative use of dimensionality expansion techniques in energy domain is also to use them for forecasting [76], anomaly detection in measuring equipment [77] and power consumption estimation [78].

IV. FEATURE STORE

In modern data infrastructures, the features produced using the techniques discussed in Section III to be used for model training, are managed by feature stores. These are data management services that harmonize data processing steps producing features for different pipelines, making it more cost-effective and scalable compared to traditional approaches [10], [79].

As depicted in Figure 1 and described in Section I a feature store ingests data, transforms it according to the instructions kept in a feature store registry, and serves features. To better illustrate how a feature transformation for Figure 1 works, we presented feature transformation as data flow in Figure 3.

As shown in Figure 3 a flow starts where a feature store takes raw data discussed II. Within a feature store, the data is transformed according to the instructions in a feature store registry. Here, the data is transformed into primitive or derived into more complex features as discussed in Section III. A feature can be built out of single or multiple sources or features. The flow ends with feature serving, where features are passed to the model(s), where each requires a different set of features to work correctly. Many different features can coexist simultaneously in a feature store, and a model may not use all features.

Certain feature stores, such as those listed in Table II, are specialized in time-series data. With those, the ML model can request data from any point in time, and specialized feature store will retrieve valid data for that timestamp and ensure there is no data leakage.

A feature store’s registry contains instructions on how every feature should be produced. These descriptions (or recipes) define what ingredients from available data sources are required to build every feature through transformation(s). Once a new feature is introduced into a registry, it becomes immediately available to other pipelines and workflows. Because of this, it fits nicely into existing continuous integration development processes and decouples feature engineering and model development.

Table II summarizes existing feature stores. It can be seen that there are three open source stores, namely Feast, Hopsworks and Butterfree and several proprietary ones. Besides containing recipes for automatically generating features, functionality for re-generation and feature serving, feature stores also decrease the engineering efforts in connecting to various data storage and delivery technologies. It can be seen from the third column of the table that they include connectors to support fast interconnection with various storage solutions (BigQuery, S3, Postgres...), and streaming platforms (Kafka, Spark). As per columns three and four, it can be seen that all open source stores support offline and online storage such as public cloud provider’s BigQuery, Azure, S3 and Snowflake or open source solutions such as PostgreSQL and Cassandra. For the proprietary feature store solutions the choice of technologies is sometimes unclear as the case of Iguzio, Molecula and Rasgo. As can be seen from the sixth column of the table, the open source feature stores can be
| Name   | Open Source | Data Sources                                      | Offline Storage                                      | Online Storage                                      | Deployment                  | Misc                                 |
|--------|-------------|---------------------------------------------------|-----------------------------------------------------|-----------------------------------------------------|-----------------------------|-------------------------------------|
| Feast  | Y           | BigQuery, Hive, Kafka, Parquet, Postgres, Redshift, Snowflake, Spark, Synapse | BigQuery, Hive, Pandas, Postgres, Redshift, Snowflake, Spark, Synapse, Trino, custom | DynamoDB, Datastore, Redis, Azure Cache for Redis, Postgres, SQLite, custom | AWS Lambda, Kubernetes, local   |                                    |
| Hopsworks | Y   | Flink, Spark, custom Python, Java, or Scala connectors | Azure Data Lake Storage, HopsFS, any SQL with JDBC, Redshift, S3, Snowflake | any SQL with JDBC, Snowflake | AWS, Azure, Google Cloud, local |                                    |
| Butterfree | Y     | Kafka, S3, Spark | S3, Spark Metastore | Cassandra | local | Apache Airflow |
| SageMaker | N         | integrates with the AWS ecosystem |                      |                                 | AWS                          |                                    |
| Databricks | Y/N     | DataGrip, Azure Data Factory, dbt, DBEaver, Delta Lake, JSON, Kafka, Parquet, Prophecy, Spark, XML, many commercial providers, custom | BigQuery, S3, Azure Data Lake, Snowflake, custom | DBFS, S3, Azure Blob Storage, custom | AWS, Azure, Google Cloud         |                                    |
| Iguazio | N           | SQL DBs, unstructured data sources N/A | N/A | N/A | AWS, Azure, Google Cloud | E2E solution |
| Kaskada | N           | Parquet, S3, plain text | Redshift, Snowflake | DynamoDB, Redis | Kaskada | define pipeline with Fenl language |
| Molecula | N           | CSV, Delta Lake, JSON, Kafka, Snowflake N/A | N/A | N/A | ? | E2E solution |
| Rasgo | N           | Azure, BigQuery, Delta Lake, RasgoQL, S3 | Cloud Data Warehouse, S3 | N/A | Snowflake, RasGO | support no-code development |
| Tecton | N           | Kafka, Amazon Kinesis, Redshift, S3, Snowflake | Snowflake, S3 | Redis | Databricks, AWS EMR | E2E solution of Feast |
| Vertex AI | N         | integrates with the Google Cloud ecosystem |                      |                                 | Google Cloud             |                                    |

V. EVALUATION

In this section we first evaluate aspects related to feature importance and feature selection for developing a machine learning model, following by benchmarks of three feature management solutions.

Throughout the section we use HUE (the Hourly Usage of Energy dataset for buildings in British Columbia) dataset [19]. It contains hourly data from 28 households in Canada, collected in different timespans between 2012 and 2020. The dataset consists of raw data, household metadata, and weather data (≈744,000 samples in total). This dataset is suitable for analyzing and predicting household energy consumption.

A. Feature importance

To assess the important of the three categories of features from Figure 2 in addition to the HUE dataset that includes domain specific, contextual and behavioural features, we also consider additional contextual features related to solar radiation and altitude produced by a model [80].

From HUE we have the energy consumption measured by IEDs and categorical variables related to the type of heating devices such as forced air gas furnace (FAFG), heat pump (HP), etc. as domain measurement. Additionally, as contextual features we consider available metadata related to the building such as the id of the residence, house orientation, type of house related to the geographical location such as region and meteorological data such as pressure, temperature, humidity and weather (e.g. cloudy, windy, snow storm). We also consider behavioural features related to weekdays and holidays (is_holiday, weekday, is_weekend). To understand the importance these features may have in estimating short time consumption for 1 hour ahead we train an XGBoost regressor and assess the assigned importance.

The results of the feature importance as learnt by XGBoost are presented in Figure 4. It can be seen that the raw instant energy consumption is the feature that contributes the most to the energy estimation. The second and sixth most important features are the mean and standard deviation of the energy generated using statistical feature engineering techniques as discussed in Section III. Contextual features such as solar azimuth and how much of the 24h in a day have passed (day_percent) are the third and fourth most important features. It can be noticed that the XGBoost considers the instant energy consumption locally and also in the public cloud.
energy consumption more than twice as important as its rolling window average with a score of 1035 compared to 488. The importance of the second and third features are between 400 and 500, the importance of fourth to seventh features is also comparable, with values between 300 and 400. Starting with the eight feature, the importance decreases more abruptly from just below 300 to below 100 while the last 12 features, mostly related to the type of heating and cooling devices used as can be seen from the legend of Figure 4, are relatively less important by an order of magnitude lower than the first. Other features, which were omitted from bar plot, show no significant importance.

Fig. 4: Feature importance score for estimating future (1h ahead) energy consumption.

Table III shows that adding additional features to the data significantly improve the estimation performance. Improvement can be observed through a consistent decrease of mean squared error of prediction (top to bottom). The first row shows that using (only current) raw values, the model achieves 0.343 kWh mean squared error. By adding the "statistical" feature set, MSE decreases to 0.327 kWh. The most significant improvement is observed when weather data is added, where MSE drops from 0.327 to 0.292 kWh. By adding building properties in addition to raw, statistical, and weather data, MSE further decrease to 0.265 kWh. By adding time feature set, MSE decrease to 0.260 kWh. Finally, a minor improvement comes from geolocation and sociological feature sets, where MSE decrease from 0.260 to 0.258 kWh.

We observe that new features can significantly improve energy consumption prediction performance. We found that new features, which may at first glance be unrelated to the energy, can significantly contribute to the model’s performance. By adding new sets of features, we improved MSE from 0.343 kWh to 0.258 kWh, which is 33% improvement.

**TABLE III: Impact of additional feature categories on the XGBoost regression model.**

| Feature set              | MSE [kWh] | MAE [kWh] | medAE [kWh] |
|--------------------------|-----------|-----------|-------------|
| raw                      | 0.343     | 0.317     | 0.146       |
| ++ statistical           | 0.327     | 0.308     | 0.148       |
| ++ weather               | 0.293     | 0.292     | 0.148       |
| ++ building properties   | 0.265     | 0.278     | 0.141       |
| ++ time                  | 0.260     | 0.275     | 0.138       |
| ++ geolocation           | 0.259     | 0.274     | 0.138       |
| ++ sociological          | 0.258     | 0.274     | 0.138       |

B. Impact of features on the model performance.

This section examines how each category of features can contribute to the model’s accuracy. The goal was an accurate prediction of energy consumption 1 hour ahead. The training data was shuffled, split using 10-fold cross-validation, and evaluated 10-times using the XGBoost regressor algorithm. Every step of the ML pipeline was seeded for a fair comparison.

Table III presents the evaluation on the impact of features on model performance. From top to bottom, each row adds a set of features. The "raw" feature set contains only instant energy consumption collected by IEDs. The "statistical" feature set adds rolling average and standard deviation for the last 10 hours. The weather feature set adds attributes regarding outside temperature, humidity, pressure, weather condition, theoretical solar altitude, azimuth and radiation. The building properties adds attributes of each household, house type, house facing direction, number of EVs, and type of heating system. The "time" feature set adds the percentage of day, week, and year elapsed. The "geolocation" set adds geographical longitude and latitude. Finally, the "sociological" feature set adds information regarding holidays, weekday, weekend, and information about region.

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We observe that new features can significantly improve energy consumption prediction performance. We found that new features, which may at first glance be unrelated to the energy, can significantly contribute to the model’s performance. By adding new sets of features, we improved MSE from 0.343 kWh to 0.258 kWh, which is 33% improvement.
This relatively short execution time is due to the size of the data of up to 744,000 rows.

The join & enrich steps with Python took the longest to complete. It took Python 1707 seconds using Pandas to merge (i.e., SQL LEFT JOIN operation) three tables together and generate new features. However, pure Python was the fastest at retrieving a subset of the merged dataset, which took 0.6 seconds. For cases when an intermediate Parquet file with all the features exceeds the system memory size, it requires extra engineering and may not scale well.

The approach with Spark was the fastest at merging datasets taking 1051 seconds, which is approximately 3 minutes faster than the pure Python approach. Faster execution is because most of the tabular data operations on Spark can utilize multiple threads and multiple workers (distributed). However, the distributed approach comes with an overhead of synchronization between workers and controller nodes, especially when flushing the output to the storage. Because of this overhead, Spark took longer, 7 seconds, to retrieve the subset of data. However, Spark would scale better with a large intermediate dataset. This is because Spark can scale in the number of workers and utilize distributed filesystems, such as HDFS and GlusterFS.

The approach with feature store is a bit different from the pure Python and Spark approaches. It took Feast to "merge" the datasets at around one second. However, Feast does not "merge" anything at the preparation phase. Instead, it checks intermediate files (i.e., Parquet files from the first stage) and constructs data samples only when requested at the retrieval stage. The burden of joining data is pushed to the retrieval phase, which is why Feast requires the longest to retrieve the subset at approximately 21 seconds. While this is the slowest retrieval time, adding hot storage (e.g., Redis) can be significantly improved, and it is expected in official documentation to be used in production deployment.

One significant benefit of feature store (i.e., Feast) is handling new incoming data. Feature store would require only processed files to be updated before new data can be accessed. The present Python and Spark approach would have to redo the merging of the intermediate dataset with all features before new samples are accessible.

VI. Conclusions

In this paper we presented a study on data models, energy feature engineering and feature management systems for developing ML based energy applications. We first proposed and presented a taxonomy for data model design of available features applicable in developing ML applications in energy domain. The three main categories of features identified in the taxonomy are: behavioral, contextual and domain specific. We then discuss techniques for feature generation and show that they can improve the performance of ML models on an energy consumption forecasting example. More recently, features are managed by dedicated systems and we analyze existing designs. We also prototyped and evaluated three complementary feature management solutions and showed that an open-source feature store solution can significantly reduce
the need to develop new data models. Compared to currently used solutions, feature store can take by up to 99 percentage points less time to process, enrich and obtain the features needed for production ready model development.

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