Automated Classification of Power Plants by Generation Type

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ABSTRACT

Generation type of power plant (e.g. steam, wind) is an important attribute in power grid and energy market studies such as bidding strategy, audit of generation mix, and accounting for load-generation matching. Recently, regional transmission organizations (RTOs) and independent system operators (ISOs) are increasingly redacting a wide range of grid and market data attributes to protect their participants' business interests. Lack of this information can prevent important power grid research.

We propose techniques to infer power plant generation types based on publicly-available market data. We develop and evaluate these techniques on data available from the Midcontinent Independent System Operator (MISO). Evaluation shows successful classification of power plants, achieving 100% precision and 99.5% recall for wind plants, and 91.7% overall accuracy. On the basis of generated power, our classification shows 100% precision and 99.8% recall for wind plants and 93.2% overall accuracy.

Our ultimate goal is to generalize to a wide range of RTOs/ISOs. We explore three feature types (bid pattern, capability, and operation), and evaluate their classification value for MISO. We also assess applicability to other RTOs/ISOs based on available market data. These studies inform the efficacy of the features for generation-type inference in other RTOs/ISOs.

CCS CONCEPTS

• **Hardware** → **Energy generation and storage**; • **Computing methodologies** → **Machine learning**.

KEYWORDS

power plants, energy market, renewable energy, machine learning, data analytics

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1 INTRODUCTION

Modern power grids incorporate plants of different generation types (e.g. gas turbine, wind) that generate and sell power every day. With the adoption of aggressive renewable portfolio standards (RPS) [6, 7, 25, 33], generation mix is shifting rapidly towards renewables with variable, correlated generation. These different operating mixes present new challenges in management (balancing, regulation, etc.), markets (price stability) and renewable absorption (curtailment, grid capacity value) [23, 24, 40]. Consequently, power plant generation type is an important attribute for modeling the dynamics and efficacy of power grids, generation, and markets. For example, generation-type labels can enable study of bidding strategy with flexible and inflexible generation[39], help adapt generation scheduling models to real-world data[10], and enable load-coupling of load such as data centers to renewable generation [11, 20, 42]. Power plant generation type is also useful for auditing actual generation by type.

Because the dynamics of renewables can disrupt power market pricing and even balancing, accurate modeling of generation mix as well as generation behavior has become an essential element of many large-scale load management, demand response, smart grid, or data center co-management studies. However, generation mix labels are increasingly difficult to obtain.

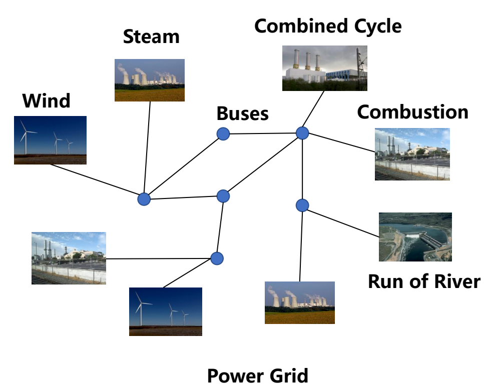


Figure 1: Modern power grids integrate power plants of different generation types with varied behavior. (Images: Public Domain)

In the United States, regional transmission organizations (RTOs) and independent system operators (ISOs) coordinate, control, and monitor the operation of power grids. According to the Federal Energy Regulatory Commission (FERC)'s rules[12], RTOs and ISOs deliver market data to FERC periodically, and usually make some market data public. Several community efforts seek to create open

Table 1: Comparison of Data Availability of RTOs/ISOs

RTO/ISO Name	Area	Plant-level Reports	Plant Generation Type
MISO	15 U.S. states and the Canadian province of Manitoba	Yes	No
PJM	All or parts of 14 eastern States and The District	Yes	No
ERCOT	Most of Texas	Yes	Yes
CAISO	California	Yes	No
ISO-NE	Six New England states	Yes	No
NYISO	New York State	Yes	No
SPP	All or parts of 14 central states	Yes	No

models and data for power grids (e.g. openmod[29], OpenEI[28]). However, with rising climate-awareness as well as spreading privatization, disclosure of detailed generation mix and market behavior has come under increasing scrutiny. For example, RTOs and ISOs have begun to omit several types of information such as per-offer pricing (LMP) and power-plant generation-type from their public data releases.

Our survey explored data availability for the seven major RTOs and ISOs in the United States: the Midcontinent Independent System Operator (MISO), Pennsylvania-New Jersey-Maryland Interconnection (PJM), Electric Reliability Council of Texas (ERCOT), California ISO (CAISO), ISO New England (ISO-NE), New York ISO (NYISO), and South Power Pool (SPP) (Table 1). All of these markets report plant-level generation offers publicly, but only one currently contains generation type of power plants. Many used to, but have ceased such release. For instance, MISO provided generation type in market cleared offer reports (settled offers), but since December 2016 no longer provides that data. The stated reason is to "ensure and preserve the confidentiality of cleared offersâĂŹ units". Removal of power plants' generation type has been noted and already hinders researchers in applying their models to latest data[9].

Our goal is to infer generation type based on available public data in order to enable richer smart grid and power market research. Our high-level approach is to identify features based on domain knowledge of generator type behavior. Next, we test the efficacy of each of these resources in various combinations in a feature vector combined with various machine learning techniques. We test the accuracy of the classifiers against ground truth (available for 2015, 2016). We also explore a multi-stage classification process to see if higher accuracy can be achieved. Our efforts produce a classifier that infers power plant generation type accurately. Specific contributions include:

- Study of power plant generation types in market reports of seven major US RTOs/ISOs reveals that only ERCOT provides power plant generation type in market reports. This demonstrates the need for generation-type inference.
- We present two approaches: one-stage classification, which directly classify all power plants into five classes, and multistage classification, which consist of classifiers for wind power plant, run of river power plant, and the rest types of power plants. The classifiers in both cases are based on three types of features extracted from market reports: bid pattern, capability, and operation.
- We evaluate the classifiers, using MISO's public data from before and after they redacted generation-type information. Comparing the performance of three widely-used machine learning algorithms, we evaluate the classification algorithm's accuracy and show that it achieves 91.7% accuracy by plant count and 93.2% by power generation.
- Exploration of generalization to other RTOs/ISOs - with our survey we identify which RTOs/ISOs release sufficient data to enable our classification techniques. We look forward to evaluation on this further data.

The rest of the paper is organized as follows. In Section 2 we discuss related work using machine learning for classification in power market/grid dynamics. Then we propose an algorithm for classifying generation types of power plants in Section 3 and evaluate its efficacy on MISO's data in Section 4. We summarize and discuss possible directions for future work in Section 5.

2 RELATED WORK

We review prior work applying machine learning for classification tasks and applications in power systems. We then discuss our work's impact on energy market and power grid dynamics research.

Classification Using Machine Learning. Machine learning technology powers many applications in modern society, especially the ones related to pattern recognition. And deep learning, a branch of it, has dramatically advanced the development of areas such as computer vision and natural language processing[22]. Among different types of data, what our problem involves is panel data, which combines cross-sectional and time series data, containing observations of multiple attributes over time for a set of power plants. From cross-sectional data side, classification tasks are widespread, such as text sentiment classification[31], credit-risk prediction[18], and user behaviour analysis[34]. From time series data side, it's more difficult to extract discriminative patterns from temporal signals for classification tasks[15], but several communities have also done a lot of work on solutions to classification tasks[15, 17, 38]. Our approach stands between the two sides: we extract both static and temporal features from the data, and regard it as a classification task on cross-sectional data.

Machine Learning Applications in Power Systems. In the area of power systems, machine learning has been used for security assessment, fault detection, measurement data analytics, and generation/load forecasting, among which we put more focus on classification tasks. Classifiers widely used for classification tasks in power systems include support vector machine[16, 30], decision tree[21], and random forest[21, 27, 37]. To our knowledge, these models have not been applied to power plant generation type classification. For input of these classifiers, feature extraction in above tasks typically relies on domain knowledge about power systems. For example, features for security assessment include voltage angle/magnitude, complex generation, and load at bus[16]. Beckel et al. propose to use electricity consumption data to classify households[2, 3] according to some pre-defined properties, and identify four groups of features from consumption data to reflect household's pattern: figures, ratios, temporal properties, and statistical properties[2]. We extract features from similar angles with different categories and find that they are efficient for our classification task.

Market and Grid Dynamics. As power grids incorporate more renewable generation such as wind or solar, and begin to phase out "dirty" power plants such as coal-fired ones, studies of power grid and energy market dynamics with different goals are emerging. Birge et al. recover market structure from MISO's data, and discuss its spatial and temporal variation, providing an analytical tool for market participants[5]. Many studies focus on the impact of changing generation mix[4, 11, 14, 19, 39]. For example, Chien et al. characterize the increasing curtailment and uneconomic power in MISO, which potentially match the increasing load of data centers[11]. We are personally interested in these studies that explore how hyperscale data centers load can be coordinated to increase effectiveness of renewable generation. However, these studies typically presume labeled generators, which are usually obtained under contracted non-disclosure agreement or through simulation settings.

In this paper, we focus on the generation type of power plants in the power grid, which is an important attribute in market and power grid models. We model the power plants with a set of well-defined features reflecting their static and temporal properties, and apply machine learning classifiers to power plant classification. The inference of generation type would significantly increase the real-world data and systems that could be studied, and enhance current market and power grid models by modeling the power plants better.

3 APPROACH

We introduce our approach for power plant generation type classification. The approach begins with a feature set designed in accord with insights into behavioral characteristics of different generation-type power plants. Next, we select three machine learning models, trying both one-stage and multistage classifications. All of this work is done on MISO market data, and validated with earlier data which MISO released with generation-types labeled. Finally, we explore where sufficient data is available for our approach, considering other RTOs/ISOs in the United States.

3.1 Dataset

We collected market data from MISO's website (years 2015-19). This data includes aggregated wind generation and real-time market cleared offers. The aggregated wind generation data contains hourly total wind generation in MISO's dispatch region. The real-time market cleared offer reports include the fields shown in Table 2. In MISO's real-time market, the delivered power and clearing prices are calculated for 5-minute intervals based on supply, demand, and security-constrained economic dispatch. This dispatch involves a complicated market optimization based on locational marginal pricing (LMP), and critical reliability and stability constraints. Power plants can submit hourly updates of their commit status or EconMax (max MW) operating parameters to the system. The 2015 and 2016 real-time market cleared offer reports contain plant generation type, providing ground truth for our study.

3.2 Power Plant Generation Types

Before 2017, MISO provided generation type labels for power plants, classifying plants into 13 types. These include five major types – steam, combustion, run of river, combined cycle, and wind (Table 3) as well as eight less common types including Diesel, Pumped Storage, Combine Cycle CT, Other Fossil, Other Peaker, Demand Response Type 1, and Demand Response Type 2. The settled bids were labeled with a unique generation-type code for each power plant. The five major plant types, shown in Table 3 account for over 99% of the dispatched energy in MISO real-time market. Therefore, we focus on these five types of power plants.

(1) **Steam Turbines** extract thermal energy from pressurized steam and use it to do mechanical work on a rotating output shaft that drives an electrical generator. Power plants with steam turbines, including fossil fuel and nuclear power plants, account for most of the power generation in MISO. The scale of generation capacities varies from several megawatts to over 1,000 megawatts.
(2) **Combustion Turbine** is another name for gas turbine. It converts natural gas or other liquid fuels to mechanical energy, which then drives a generator producing electric power. A key characteristic of combustion turbines is their ability for rapid ramp (turn on and off) within minutes. Consequently single cycle combustion turbine plants usually operate for peak hours or unscheduled demand, generating even only a few dozen hours per year. In some cases, they might operate longer in areas without base-load or other load following power plants, whose cost of power is often higher than steam turbines. Both types of operating modes for combustion turbines can be found in MISO.
(3) **Run of River Hydroelectricity** is a hydroelectric system that harvests energy from flowing water to generate electricity. It does not require a large dam or reservoir and exploits the natural flow rate of water instead. Run of river plants have less negative environmental impact compared with dam-based hydro-power plants, and thus are an increasing generation source in Midwest and Canada. This type of power plant is usually built where there are water flows with substantial flow rate and a grade that speeds river water significantly. Typical capacity of run of river power plants range from 100 kilowatts to 50MW or even larger [1].
(4) **Combined Cycle** plants use both gas and steam turbines to generate power. Waste heat from the gas turbine is used to create steam, and then a steam turbine generates extra power. The combination increases overall efficiency compared with a single gas turbine. The hybrid structure of combined cycle power plants brings mixed patterns to generation and bidding. MISO considers a combined cycle plant consisting of

Table 2: Description of Fields in Real-time Cleared Offers (2016 version, Source: MISO)

Column Name	Description
Unit Code	Unique numerical identifier for the power plant (unit)
Unit Type	A number indicating unit's generation type (only available for 2015-16 data)
Mkthour Begin	Interval start time for real-time offer
Cleared MW/LMP (1-12)	Delivered power (MW) in the interval and the cleared price (\$/MW)
Economic Max (EconMax)	The highest output available from the unit for economic dispatch in the interval
Unit Available Flag	Indicates whether unit is available and can be scheduled
Economic/Emergency/Must Run Flag	Indicates the unit's commit status (economic dispatch/emergency scheduling/self-scheduling)
Price/MW (1-10)	Bid price and offered power pairs (price curve)
Slope	Describes the shape of price curve shape as slope or block

Table 3: MISO Real-time Market's Dispatched Energy (TWh) and Number of Power Plants by Generation Type (2016)

Unit Type	Generation Type	Energy	Number
4	Steam Turbine	413.17	357
27	Combustion Turbine	54.63	415
41	Run of River	7.90	65
52	Combined Cycle Aggregate	81.17	55
61	Wind	46.83	209
Others	Various	2.60	117
Total		606.31	1218

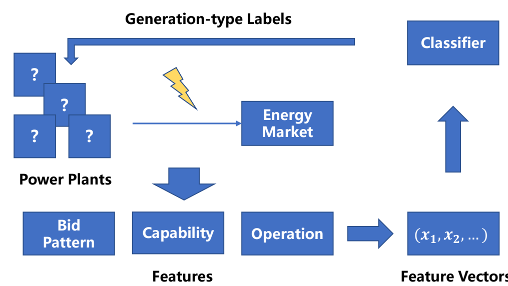


Figure 2: Overview of Problem and Approach

gas turbines and steam turbines as a single unit, while some other power grids consider them as separate units.

(5) **Wind Turbines** generate electricity from wind. The wind turns the propeller-like blades of a turbine around a rotor, spinning the generator. Because there is no fuel cost, a utility-scale wind power plant has low generation cost, and often bids low prices. However, availability of generation capacity varies, depending on weather patterns. In MISO, wind is the largest source of renewable power, accounting for about 10% of the generation[11].

Distinct characteristics of these five major plant types are reflected in power plants' generation offers, providing a foundation for identifying a power plant's generation type. We will discuss more details about how that generation type is reflected in market offers (bids) in Section 3.4.

3.3 Problem Formulation

We define the power plant classification problem as identifying power plant generation type based on its behavior in the power market. This means assigning generation-type labels to each of the power plants.

A power plant's behavior in the power market is extracted from market reports. More specifically, we focus on five labels - steam turbine, combustion turbine, run of river, combined cycle aggregate, and wind because these five generation types account for nearly all generation in MISO (99.6% in 2016). Power plants are denoted as"units" in the real-time market cleared offer reports.

Our high-level approach is to identify features based on domain knowledge of generator type behavior. For example, the ramp rate characteristics of gas turbines. Next, we test the efficacy of each of these resources in various combinations in a feature vector combined with various machine learning techniques. We test the accuracy of the classifiers against ground truth (available for 2015, 2016). We also explore a multi-stage classification process to see if higher accuracy can be achieved.

3.4 Defining Features

To extract the features of power plants, we begin by analyzing real-time cleared offers. These offers reflect production, bid price, and operation status. Based on knowledge of typical generator operation for each type, we construct features which we believe will be predictive of generation type. For example, generators with fuel cost will exhibit a lower bound on bid prices set by their fuel cost. Others may be unrestricted price takers. Another example, steam turbines' ramp rate will be limited by intrinsic physical properties such as thermal mass.

3.4.1 Bid Pattern. Bid pattern can be indicative of generation type. Bids are constrained by operating cost, which for steam, combustion, and combined cycle means that fuel cost imposes a non-zero floor on bidding. Specifically, we expect that run-of-river and wind generators that have no per-MW incremental costs can economically bid prices all the way down to zero. Furthermore, their inflexibility in generation - production driven by natural phenomena such as the rate of water flow in the river – means that they are eager to garner whatever revenue they can; even at a very low price. Such generators are often called "price takers" because they bid so low, or in the market clearing they accept the prices set by the equilibrium set by other bidders. To exploit this knowledge, we define a feature, called "low bidder", when a generator bids either "noprice" or < \$5 per MWh in 95% of the days.

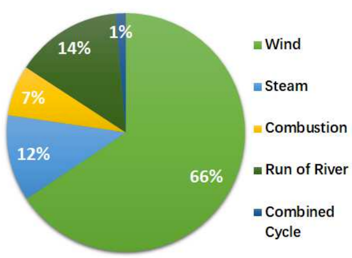
To capture the notion of the fuel-cost limit, we define a second feature called "average bid start". This feature is the mean value of the price for the first step in the bid curve over all of the operating hours. A low first step indicates a willingness to generate power at that low price. Generators that have fuel cost will generally require a higher initial price.

These features are documented in Table 4.

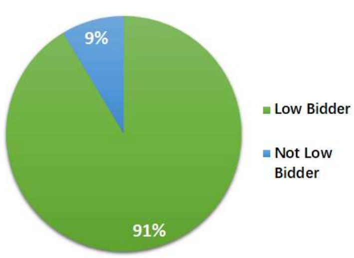
Table 4: Bid Pattern-related Features

Feature	How to Measure
Low Bidder	Boolean Variable (0/1)
Average Bid Start	$Mean(Price_1(t))$

From the market reports, we find that 310 of 1218 power plants match the "low bidder" pattern, and 66% of them are wind power plants. Within the wind power plants, 91% of them match this "low bidder" feature, which suggest that this feature can be used for identifying wind power plants. This phenomenon is consistent with the fact that wind power plants have very low fuel cost and long-term observation[35]. On the contrary, some combustion turbine power plants, which may only operate during peak hours, usually start bidding at a high price, even higher than \$300/MWh.



(a) Breakdown of Power Plants with "Low Bidder"



(b) Breakdown of Wind Power Plants

Figure 3: Breakdown of Power Plants with "Low Bidder" by Type and Breakdown of Wind Power Plants by Bid Pattern

3.4.2 Capability. In our work, a power plant's capability refers to two terms: maximum generation capacity and ramp rate (rate of changing output). Such properties are largely determined by the generator type, and thus they reflect generation type. For example, because of the intense energy released by nuclear reaction, a nuclear power plant's generation capacity can reach over 1000 MW, which is much higher than the run of river power plant's capacity (typically less than 100 MW). However, the run of river power plant has much higher ramp rate than the nuclear power plant's, as it's easier to adjust flow of water than to control nuclear reaction.

We define four features to capture power plants' difference in capability: generation capacity (Figure 4) with two related statistical features, and ramp rate (Table 5). Power plant's generation capacity is estimated by the maximum of Economic Max over time[1], while ramp rate is estimated by maximum difference in generation between two consecutive 5-minute intervals. In order to measure the flexibility of capacity, the coefficient of variation (CV) and relative range of economic max are added, describing dispersion and range of capacity under economic dispatch.

Table 5: Capability-related Features

Feature	How to Measure
Generation Capacity	$Max\{EconMax(t)\}$
Capacity's Dispersion	EconMax's Coefficient of Variation
Capacity's Range	EconMax's $Range/Mean$
Maximum Ramp Rate	$Max\{\lvert Cleared\ MW_{i+1} - MW_i\rvert\}$

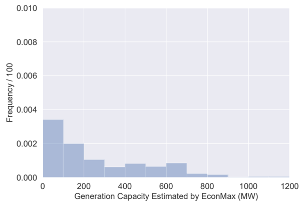
3.4.3 Operation. The generation type influences a power plant's operation. Within the operation information contained in MISO's real-time cleared offers, there are three types of commit status: economic, which means the power plant is available for economic dispatch; emergency, which means the power plant will not be scheduled unless the RTO/ISO calls for Max Emergency generation; must run, which means a power plant will always supply electricity to the power grid. "Emergency" is usually set for combustion turbine power plants for its rapid start, while nuclear power plants are usually set as "Must Run" because they are averse to being turned off and on[36]. For each power plant, We compute the ratios of three status and define them as features.

In addition to commit status, we define the "dispatched intervals" feature with the mean value of 5-minute intervals in which electricity is dispatched. This feature reflect the how often a power plant is producing power, which also indicates a power plant's type. For example, many combustion turbine power plants only operate during load peak hours, while steam turbine power plants usually produce power in more intervals as base-load power plants because it takes much longer for them to start up or shut down.

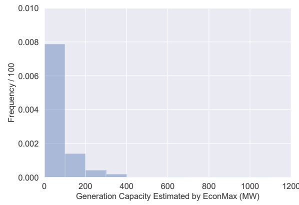
With MISO's hourly wind generation, we can compute the correlation between each power plant's hourly generation and the hourly grid total, defining a feature called "correlation with wind":

$$COR_{i,wind} = \begin{cases} \frac{cov(Gen_i, Wind)}{var(Gen_i)var(Wind)}, var(Gen_i), var(Wind) \neq 0 \\ 0, otherwise \end{cases}$$

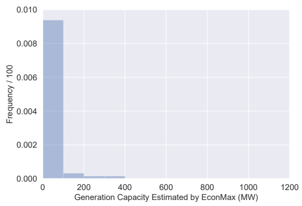
[1]Similar as [11], we exclude the power plants that do not bid Economic Max.



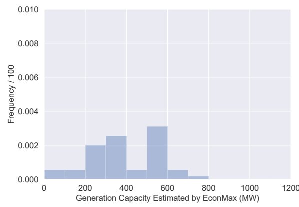
(a) Steam Turbine



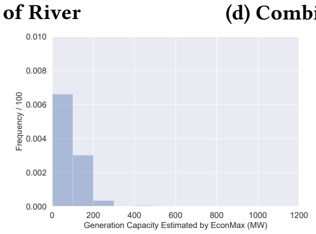
(b) Combustion Turbine



(c) Run of River



(d) Combined Cycle



(e) Wind

Figure 4: Distribution of Generation Capacity (MW) by Generation Type

where Gen_i denotes the array of power plant i's hourly generation, and $Wind$ denotes the array of hourly total wind generation. On the one hand, as each wind power plant contributes to the aggregated generation, we expect that the average correlation coefficient between a wind power plant's generation and total wind generation will be positive. On the other hand, as other types of power plants such as steam and combustion may compensate decreased wind generation by increasing generation, a negative correlation may indicate that a power plant is not driven by wind. This inference is verified by calculating all correlation coefficients between each power plant's generation and total wind generation (Figure 5).

These operation-related features are documented in Table 6.

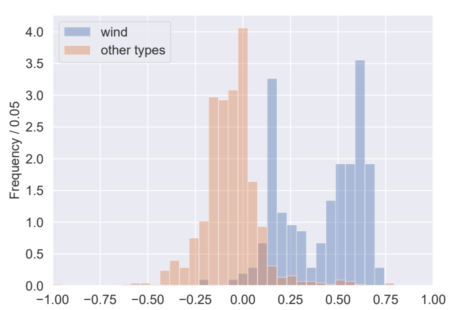


Figure 5: Distribution of Correlation Coefficient with Total Wind Generation by Generation Type

Table 6: Operation-related Features

Feature	How to Measure
EconRatio	Ratio of "Economic" hours
EmerRatio	Ratio of "Emergency" hours
MustRatio	Ratio of "Must Run" hours
Dispatched Intervals	Mean of Dispatched Intervals
Correlation with Wind	Correlation Coefficient

3.5 Classifier Approaches

Considering the dataset size and the distributions on different features, we consider support vector machine (SVM), decision tree, and random forest approaches for classifiers. All of these approaches support nonlinear classification. We consider both one-stage and multistage classification. To implement this, we use scikit-learn[32] and use grid search for parameter tuning. We build the feature space from the features, and represent each power plant i, as a vector $X_i = (x_1, ..., x_n)$, where x_k denotes the value of k-th feature. After classification, the power plant i is assigned a label y_i, where $y_i \in$ {steam, combustion, run of river, combined cycle, wind}. We apply each of these approaches and evaluate their efficacy on accuracy, precision and recall.

Support vector machine (SVM)[13] is a learning model based on maximizing the gap between two classes. It is widely-used and is a robust and accurate method[41], which does not require large-scale training data. "Support vectors" define hyperplanes that split two classes of data. In order to adapt SVM for nonlinear classification, we map the data into a higher dimensional space with the radial basis function (RBF) kernel.

Decision tree is a tree-like model of decisions and corresponding consequences, whose leaves represent the classes that divide samples. Each split uses a feature and value, selected based on specific standards (e.g. Gini impurity). Typical applications limit maximum tree depth and minimum number of samples to justify splitting a node. Significant advantages of decision tree include good interpretability, few data preparation requirements, and ability to handle different types of data.

Random forest is an ensemble of decision trees. Each decision tree is trained on data sampled randomly and independently, and only a random subset of features can be selected during each round candidate split in tree construction, which completes an internal feature selection. After training, the classification result is determined by averaging different trees' prediction (scikit-learn implementation). The import of randomness decreases the correlation between decision trees in the forest, and thus decreases the possibility of overfitting and makes it more robust with respect to noise[8].

Decision tree and random forest support multi-class classification inherently, while SVM is extended through one-vs-one strategy in scikit-learn, which constructs one classifier per pair of classes. We evaluate the performance of each type of classifier in Section 4.

3.6 Classification Procedure

With the extracted feature sets and classifiers, we propose two classification approaches: one-stage classification and multistage classification. The feature selection and performance will be evaluated in Section 4.

3.6.1 One-stage Classification. In one-stage classification, the feature vectors representing power plants are directly classified into five classes (wind, steam turbine, combustion turbine, run of river, and combined cycle) by a machine learning classifier (Figure 6).

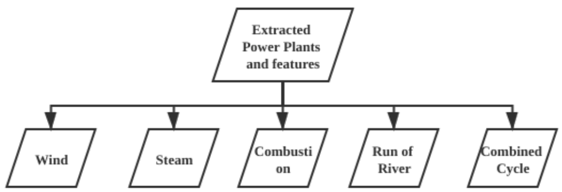


Figure 6: One-stage Classification

3.6.2 Multistage Classification. Our multistage classification uses three stages (Figure 7). In the first stage, we separate wind turbines from others mainly based on the "low bidder" pattern and correlation with total wind generation. In the second stage, the non-wind power plants are further separated into run of river vs other types, using another subset of features. Finally, the remaining power plants are classified into steam, combustion, and combined cycle. The classifier in each stage is trained with corresponding classes of power plants from labeled data.

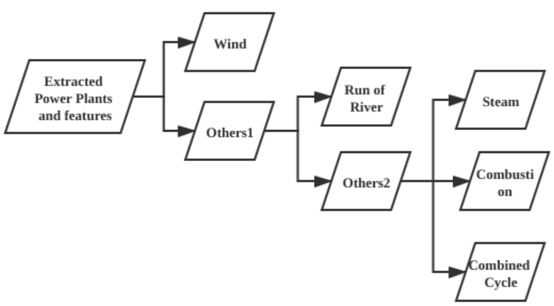


Figure 7: Multistage Classification

3.7 Transferrability

An important goal is for our generation-type inference to be widely usable, to be "transferrable" to other RTOs/ISOs. To assess feasibility, we checked whether the data needed to support the classifier features is available. Table 7 shows the results for several RTOs/ISOs. Across the group, there are significant differences in the information available. For example, while PJM, ERCOT, ISO-NE, and NYISO provide data that appears sufficient for all three of our feature types (bid-pattern, capability, and operations), SPP and CAISO only provide limited information in plant-level market reports and thus present challenges for applicability of the classifiers.

While differing in advance time (e.g. day-ahead, real-time), the reports from PJM, ERCOT, NYISO and ISO-NE include similar attributes. All lack the power dispatch quantity for 5-minute intervals, potentially an important obstacle. In addition, PJM's reports lack the commit status flag. Therefore, transferring classification capability will require workarounds. Significant new feature opportunities include no-load and start-up cost.

None of these RTOs/ISOs except ERCOT provide the generation type of power plants, the objective of our classification, in plant-level offer reports.[2] This means we will have to train supervised learning classifiers on data from other RTOs/ISOs and apply those classifiers to these RTOs/ISOs' generators.

4 EVALUATION

For both one-stage classification and multistage classification, the machine learning classifiers are trained on 80% of the 2016 data with 20% reserved as a validation set. We use the 2015 data as a test set. We also present inference results for 2018 and 2019.

4.1 Metrics

We evaluate classifier performance on standard metrics for classification tasks: accuracy, precision, and recall. Two weightings are considered – the number of power plants and power generation.

For the two-class classification, the *confusion matrix* has four quadrants: *true positives* (TP), *false positives* (FP), *true negatives* (TN), and *false negatives* (FN) (Table 8). For example, in the first stage of multistage classification, TP denotes the number of correctly classified wind plants. FP counts the number of plants with other generation types that are misclassified as wind. FN counts the number of wind plants that are misclassified as other types, and finally, TN denotes the number of correctly classified power plants with generation types other than wind.

Accuracy is the percentage correctly classified, that is:

$$Accuracy_{two-class} = \frac{TP + TN}{TP + FP + FN + TN}$$

Precision and recall of a specific class are defined as:

$$Precision_{ClassA} = \frac{TP}{TP + FP}$$

$$Recall_{ClassA} = \frac{TP}{TP + FN}$$

which respectively denote the probability that a sample classified as Class A truly belongs to Class A, and probability that a sample belonging to Class A is classified as Class A.

For classification problem with K classes, the corresponding confusion matrix consist of K^2 elements, and each element n_{ij} denotes the number of samples with specific true label i and predicted label j. The overall accuracy is defined as:

$$Accuracy_{K-class} = \sum_{i=1}^{K} \frac{n_{ii}}{n_{total}}$$

The above metrics can be directly applied to classification of power plants. If we associate generation with each plant, we can

[2]Note that generation type of power plant is listed in PJM's documentation, but they have since removed this from historical and current data.

Table 7: Data-availability to Derive Features in Other RTOs/ISOs

RTO/ISO Name	Bid Pattern	Capability	Operation	Possibility of Transfer	Main Modification
PJM	Yes	Yes	Partial	Strong	Remove commit status, dispatched intervals
ERCOT	Yes	Yes	Partial	Strong	Remove dispatched intervals
CAISO	Partial	No	Partial	Low	
ISO-NE	Yes	Yes	Partial	Strong	Remove dispatched intervals
NYISO	Yes	Yes	Partial	Strong	Remove dispatched intervals
SPP	Yes	No	No	Low	

Table 8: Confusion Matrix of Two-class Classification

		Predicted Label	
		Class A	Class B
True Label	Class A	TP	FN
	Class B	FP	TN

weight results based on power generation in similar fashion with the same metrics.

4.2 One-Stage Classification Results

To isolate their benefits, we divide the features into three subsets:

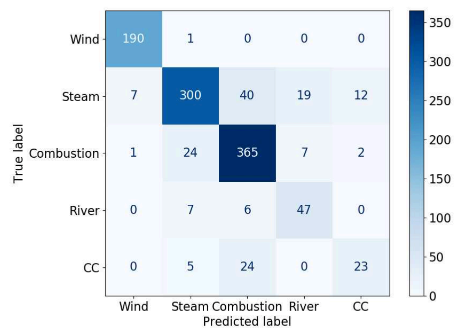
- **Subset 1:** Basic features from capability and bid pattern, including generation capacity, correlation with wind generation, maximum ramp rate, and average bid start.
- **Subset 2:** Statistical features from capability and operation, including EconMax's coefficient of variation and relative range, mean value of operating intervals.
- **Subset 3:** Features from operation, including ratios of three commit status.

Table 9 presents improvement in accuracy for classifiers as features are added. Improvement shows the features are effective. The average results are given for decision tree and random forest because of their randomness. Among the classifiers, the ranking changes as we add features. With the full feature set, random forest performs best achieving 91% accuracy, followed by SVM at 85.6% and decision tree at 85.1%. Random forest outperforms decision tree robustly, reflecting its advantage as an ensemble of decision trees.

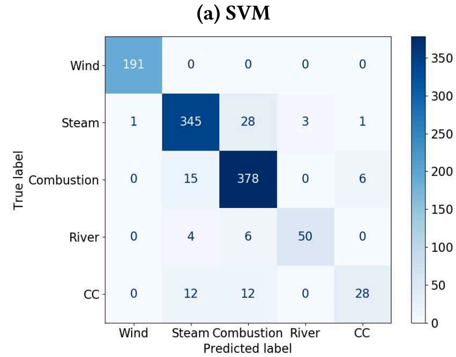
Table 9: Changes of Overall Accuracy on Test Set in One-stage Classification

Classifier	Subset 1	Subset 1, 2	Subset 1, 2, 3
SVM	79.4%	83.7%	85.6%
Decision Tree	80.0%	82.3%	85.1%
Random Forest	82.5%	87.6%	91.0%

We show confusion matrices for each of the top two classifiers, SVM and random forest, in Figure 8. It's noteworthy that random forest achieves 99.5% accuracy and 100% recall on wind power plants, showing that our approach identifies wind power plants effectively. The confusion matrices indicate that random forest outperforms SVM on precision and recall for all types of power plants. They also clearly identify the areas where confusion (incorrect classification) is occurring. Because of its good performance, we select random forest for further analysis. From the matrix, we find 40% of combined cycle plants are misclassified as steam or combustion power plants, which we will discuss in Section 4.4.



(a) SVM



(b) Random Forest

Figure 8: Confusion Matrices for One-stage Classifiers: SVM and Random Forest. (CC = Combined Cycle)

We revisit the results of the random forest classifier, using the actual power generation over the year to weight the results. This weighting is useful because we are often interested in the fraction of power generated that comes from different sources – fuel mix or generation type mix. The results of this weighted assessment is presented in Figure 9, showing that random forest achieves 91.6% overall accuracy on classifying the power generated.

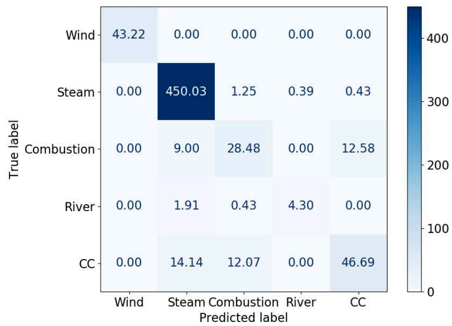


Figure 9: Confusion Matrix for One-stage Random Forest Classifier, weighted by Power Generation (TWh)

In the weighted generation, several generation types including combustion and run of river are challenging for precision and recall, achieving poorer results than in the base assessment that used numbers of power plants. The reason for the difference is that each plant has a different amount of generation. Thus, weighting with power generation shifts the balance between correct and incorrect classification. For example, in test set, 93.3% (56 of 60) of run of river power plants bid Economic Max < 100MW, but the one with most generation, which is misclassified as steam turbine power plants, account for about 11% of the generation.

4.3 Multistage Classification Results

Given our positive experience with random forest, we select it for each stage in the multistage classification. We analyze the complete feature set described in Section 3.4, and begin by selecting the most important features using scikit-learn's feature "importance" output.

In the first stage, plants are classified into two classes: wind and non-wind. The most important features selected by importance include low price pattern, correlation with total wind generation, CV and relative range of Economic Max, and average dispatched intervals. For wind power plants, the precision and recall achieve 100% and 99.5% respectively (Figure 10). These excellent results provide a strong basis for later stages.

Table 10: Confusion Matrix of Stage 1 (Wind)

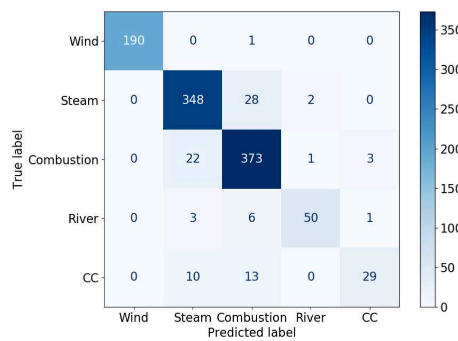
		Predicted Label	
		Wind	Non-Wind
True Label	Wind	190	1
	Non-wind	0	889

In our second stage, the non-wind power plants are classified into run of river and non-run of river types. The result corresponds closely to our results in the one-stage classification, with 94.3% precision and 83.3% recall for run of river. The most important features include maximum and coefficient of variation of Economic Max, average bid price start, average running intervals, and ratio of "Must Run" hours. Typically, a run of river power plant operates in most intervals with stable capacity and low bid start, consistent with the properties of river water flow.

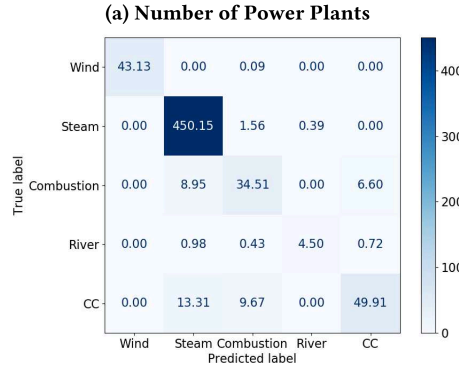
Table 11: Confusion Matrix of Stage 2 (RoR = Run of River)

		Predicted Label	
		Run of River	Non-RoR
True Label	Run of River	50	10
	Non-RoR	3	826

Finally, for the last three types (steam, combustion, and combined cycle), our results show that all of the remaining features are needed to achieve the best performance. The overall confusion matrices of power plants and generation are shown in Figure 10. At 91.7% and 93.2% overall accuracy respectively, these results are slightly better than the results using one-stage classification (91.0% and 91.6%). In particular, the power weighted results are 1.6% better, with improvements on precision and recall of combustion turbine, run of river, and combined cycle (Table 12).



(a) Number of Power Plants



(b) Power Generation Weighted

Figure 10: Confusion Matrices of Multistage Classification Results using Random Forest (Generation Unit: TWh)

We applied our classifier to MISO's 2018 and 2019 (through November 10, 2019[3]) generation and present the results in Table 13. Where possible, we use other data items from MISO to validate our results. First, in 2018, the energy (52.18 TWh) generated by the classifier-labeled wind plants matches the total wind generation (50.23 TWh) in MISO's annual generation fuel mix. The total energy (572.72 TWh) generated by the plants the classifier labeled as

[3] This is the latest data available as of this time of writing.

Table 12: Precision and Recall of Different Generation Types (TWh) on 2015's Data, by Multistage Classification

Type	Actual	Classified	Precision	Recall
Wind	43.22	43.13	100%	99.8%
Steam	452.10	473.39	95.1%	99.6%
Combustion	50.06	46.17	74.6%	68.9%
Run of River	6.64	4.89	92.0%	67.9%
Combined Cycle	72.90	57.23	87.2%	68.5%

steam, combustion, and combined cycle matches the total generation (564.84 TWh) by coal, gas, and nuclear. Second, the growth in generation fractions of both gas and wind turbines is consistent with reported trends in generation mix change in MISO[26]. These close matches indicate that the classifiers are effective. Of course our inference results cannot be fully validated for 2018 and 2019, as their raison d'etre is that MISO does not release enough information for us to do so. This shows the value of our work, providing plant-level generation type labels that enable detailed grid modeling by generation type in studies of real-world power grids.

Table 13: Inference Results on 2018 and 2019 Generation (RoR - Run of River, CC - Combined Cycle, Unit: TWh)

	Wind	Steam	Combustion	RoR	CC
2018	52.18	459.98	49.70	5.65	63.04
2019 (to Nov 10)	49.60	352.39	52.54	5.26	66.85

4.4 Discussion

Some aspects of the data are challenging for classification. We discuss some of our efforts to improve accuracy and several intrinsic challenges in the generation-type classification task.

4.4.1 Balanced Weights. Assigning different weights to different classes is a common solution to data imbalance[43]. We tried assigning balanced weights to two minor classes, run of river and combined cycle, and observed an increase in recall. However, the changes caused plants with other generation types to be misclassified as run of river or combined cycle, producing a decrease in precision. After some experimentation, we conclude that assigning balanced weights is not productive with our current feature set.

4.4.2 Identifying Combined Cycle Power Plants. Among the five major generation types, recall for combined cycle power plants is relatively low. About 40% of combined cycle plants are misclassified as steam turbine or combustion power plants. There are two possible explanations. First, the features we used may not be designed well enough to differentiate combined cycle plants from other types. In short, we may need additional features (or additional data) to increase classification accuracy. A second possibility is that the labels may be overlapping – on the basis of behavior. MISO chooses to label combined cycle plants as a distinct class. However, a better approach might be to assign labels for the stages of generation that are being combined – combustion turbine and steam turbine. At present, the combined cycle plants have attributes similar as steam turbine power plants' or combustion turbine power plants', producing lower accuracy.

4.4.3 Transferrability. The results of one-stage classification and multistage classification are close. However, we get further understanding of what features work for specific classes by dividing the classification stages. In addition, the results in Section 4.2 show that our approach can achieve high accuracy with only a subset of features. This suggests that our features and classifiers can be transferred to similar data from other RTOs/ISOs.

4.4.4 Benefits for Power Grid Research. The high accuracy of our power plants classifier means that generation type can be effectively determined for power plants – even when RTOs/ISOs do not report it. This accuracy holds when weighted by the quantity of power as well. This enables a wide range of power grid modelling research, exploring challenges such as - what have been the impact of rising renewable fraction to date, what fraction of renewable power is absorbed by the grid (versus curtailed), what will happen if renewable fraction increases further, how load variation patterns help or hurt renewable absorption, when large-scale storage will become necessary, when it might be economically viable, and more. Specifically, the classification data may enable study of current grids in detail, enabling setting parameters generation mix more precisely. Another possibility is that models such as [39] can be verified on more real data with classified power plants.

5 SUMMARY AND FUTURE WORK

We present the design, implementation, and evaluation of an approach for automated classification of power plants by generation type. Using three types of features derived from MISO power market data (bid pattern, capability, operation), our multistage approach achieves high accuracy on 1081 power plants in MISO (91.7% overall accuracy) and corresponding generation amounts (93.2% overall accuracy). The one-stage classification achieves similar results. Precision and recall for the classifiers are also assessed. The ultimate objective is to generalize this approach to fill critical information gaps at other ISOs. To that end we survey the data available for 6 other major RTOs/ISOs in the United States, and conclude that our approach can be adapted to four with minor modifications.

Future directions include application and adaptation of the classification scheme to other ISOs - both within the United States, and more broadly from around the world. We will adapt our approach and evaluate its performance on data from other major RTOs/ISOs. Further, the generation mix by fuel type is available in many RTOs/ISOs' data, while plant-level fuel type is unavailable. We have shown the feasibility of inferring a power plant's generation type with supervised learning methods. Perhaps it is possible to infer generation-type with unsupervised learning.

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