Intermittent Power Forecast Data Models for The Interdisciplinary Analysis of Energy Systems

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ABSTRACT

Current electrical system operators have operating procedures that no longer handle the unpredictable and varying loads of modern consumer demand and generation by renewables. In systems with high penetration of solar power, it is important to know the amount of power being generating for generator scheduling and determining operating reserve margins. This project aims to make intermittent energy more feasible for electrical distribution systems. Power system operations require intermittent power forecasts for multiple daily operations. It is difficult to decide how to schedule renewable energy generators when presented with so many different representations of the inherent uncertainties. To standardize intermittent power forecast data models, we need to find consistent definitions of characteristics of using power systems analysis and simulations to store forecasts such that power forecasts are replicable and comparable in power operation analysis. One way to store data is in a data model. A data model is defined as a simple container format used to describe and package a collection of data for the purpose of sharing between tools and people. Over the various operational manuals and academic papers, there was inconsistent language surrounding power forecasts and how they were used. There were two different spheres of rhetoric around power forecasts; an academic sphere and a system operators sphere. Additionally, within the review of the literature, I also identified other types of attributes that might be beneficial to include within the data model. Unfortunately, this data model was difficult to implement.

KEYWORDS

Solar power forecasting, grid integration, power system operations, inherent uncertainties, power forecast modelling

INTRODUCTION

Centered around coal-sourced generators, current electrical system operators have operating procedures that no longer handle the unpredictable and varying loads of modern consumer demand and generation. Currently, we are experiencing a paradigm shift from electricity sources that are environmentally unsustainable, such as coal, towards more sustainable technologies. Some of these sustainable technologies, such as solar panels, create decentralized power. Decentralized power is characterized by generation of power closer to demand centers (Kaundinya et al. 2009). Sources of decentralized power tend to therefore be renewable energies, such as solar. The contribution of renewable energy to the power flow is variable and unpredictable, forcing previously passive electrical grid operation to become more active (Palizban et al. 2014). System operators need to refine monitoring, control and protection protocols so that they can be more aware of the state of their system to maintain power quality.

A key factor to maintaining continuous electricity flow to consumers is ensuring that real and reactive power being consumed equals the real and reactive power being produced within the system. One way a system operator makes sure that power created equals power demanded is by monitoring frequency. Operators keep frequency at the United States standard: 60 Hertz. This frequency was chosen long ago, and every part of an AC grid must be synchronous with it. If frequency starts to increase, then there is too much power being generated and the system operator, therefore, shuts down some generators. If the frequency starts to decrease, then there is not enough power being generated and the system operator turns on more generators. Each control area is responsible for regulating frequency. Voltage is also an indicator of when generation and load are not balanced. System operators try to keep voltages nice and steady. Low voltages across transmission lines can be dangerous because the large current associated leads to overheating of power lines. Power lines can sag, as a result, and are more prone to starting fires atop any trees close by. When there is an unexpected loss of a generator, operators have to act quickly to restore the generator and load balance. To do this, they tap into the power being produced by already online reserve generators (von Meier 2006, Savaghebi et al. 2013, Stewart et al. 2014, Kirby 2017).

System operators choose reserve levels in many ways, but usually are based on risk and the reserve cost associated. One way is setting a threshold for a risk attribute. System operators set a value for the maximum acceptable risk. They iterate through different reserve levels until they reach a risk lower than the threshold, without taking into account reserve costs. Another method to choose reserve levels is the Equivalent Cost Approach. It uses a constant tradeoff between reserve cost and associated risk. A tradeoff is how much cost the systems operator is willing to decrease in exchange for an increase of risk. Alternately, a systems operator could use the Value Function Approach. This approach builds an individual value function for each criterion and weights each to build a function that, when maximized, leads to referred reserve levels (Matos and Bessa 2011a). There are also uncertainties within the system that the systems operator must plan for to ensure power quality.

Originally, there are two types of uncertainties systems operators have to consider. Load uncertainties refer to the "duck-curve," which predicts the amount of energy that is going to be consumed at a certain time on a specific day of the year. The duck curve depicts the net demand load that represents the amount of conventional generation plants that will need to be online during the day in a high photovoltaic (PV) injection power system. The shape of the curve has a distinctive dip corresponding to the middle of the day due to the increase in generation due to increased generation from PV. This curve has a Gaussian distribution with a given standard deviation and zero mean that does not need to change if the uncertainty has a nonparametric representation (Obi and Bass 2016). The second kind of uncertainty concerns generation. It is a probability mass function, which is a discrete probability distribution of the possible capacity states (von Meier 2006, Matos and Bessa 2011a). This uncertainty has been explored extensively to the point where systems operators can actually predict how much electricity will be generated through conventional means, such as coal generation. Solar generation, on the other hand, has a greater amount of uncertainty associated with it.

In systems with high penetration of solar power, it is important to know the amount of power being generating for generator scheduling and determining operating reserve margins (Bessa et al. 2012). As a result, technical reconsiderations for determining measurement strategies to inform analytic study of distribution circuits and to help predict future needs from increasing penetration levels of distributed energy resources were required (von Meier and Rodriguez 2013). System operators would ideally use probabilistic approaches that include the risk associated with the solar power forecast error to reserve assessment to solve economic dispatch. Some probabilistic approaches assume that the forecast error has a Gaussian distribution. To estimate the increase in hourly load-following reserve requirements calculate the standard deviation of the combined wind and load uncertainty as that of the sum of the two independent Gaussian random variables (Holttinen 2005, Strbac et al. 2007). Other approaches do not assume uncertainty has any distribution (Soder 2004). Most methods, however, compute the reserve requirements with a reference risk level defined *a priori* (Matos and Bessa 2011a). Unfortunately, there is a gap in operational practices that account for the risks associated with the solar power forecast error.

This project aims to make intermittent energy more feasible for electrical distribution systems. We explore how system operators can use power forecasts to determine when to prepare for sudden and unexpected loss of generators. In particular, we hope to develop a computational tool to assess operational risk within a system that has high penetration of renewables. By focusing on these systems, we expect to be able to help system operators make more reliable decisions in real time about the amount of power is generated with renewable resources. The ability to measure how certainly a system operator can assure electrical security—no unscheduled blackouts will lead to a greater understanding of how renewable energy, as a whole, affects electrical distribution systems. Thereby encouraging a greater amount of renewable generation and a more sustainable future.

BACKGROUND

The larger goal of this study is to create a sustainable, greener cleaner future and therefore it is imperative to turn to renewables but switching to them has consequences. The intermittent sources of energy or renewable energy in this paper refers to solar and wind specifically. They require robust prediction methods to integrate into power system operation because they are variable according to climate. One way to predict how much power a renewable resource might generate is through power forecasts.

Power forecasts are made by taking some power information weather information and site information. This forecast is how power plants mathematically represent how much power will be produced and forecasts are used by power system operators and researchers alike. Weather data, site information, and power source information are used to calculate power predictions (Giebel and Kariniotakis 2017). Note that the model is not agnostic about what statistical model is used to produce the forecast. Power system operators, however, are agnostic to the statistical method deployed in a forecast, and instead focus on only by how the forecast is presented and the question the forecast is trying to solve.

Power system operations require intermittent power forecasts for multiple daily operations. Operations make sure electric generation exactly meets load demand otherwise blackouts will occur. Operations include: generator scheduling, operating reserve levels, voltage regulation, and frequency regulation. In all, they ensure grid stability but as renewable injection increase, we have to rely more on power forecasts which have inherent uncertainties.

To illustrate the benefits of using power forecasts, consider the timeline for real time energy imbalance markets. These markets try to balance generation and load by minimizing ancillary services. Ancillary services are generators paid to be online and ready just in case there is not enough energy to meet demand. Market dispatches resources across balancing areas to balance energy minimizing ancillary services (Mazzi and Pinson 2017). Kaur et al. (2016) ran a multi-objective optimization simulation of an energy imbalance market, we directly with generation and demand forecasts, outages, resource schedules, economic bids, dynamic contingencies and interchange schedules. The power forecast was used in a market that was described by looking ahead 4.5 hours with 15-minute intervals. The outcome of using this power forecast was reduced operating reserve capacity which reduced costs and automatic dispatch and improved reliability (Kaur et al. 2016).

Still, the United States is starting to see renewable generation curtailments on the rise. Curtailment is defined as when a power plant could generate more energy, but the system operator tells the power plant to generate less or not at all. In Texas, Electric Reliability Council of Texas (ERCOT) reported they had 20% wind generation capacity in 2016, but only 15.1% of wind energy was used ("ERCOT Quick Facts" 2017). Similarly, in 2015, the California Independent Systems Operator (CAISO) was forced to curtail more than 187,000 total MWh of solar and wind generation. And in 2016, that number rose to more than 308,000 MWh ("California ISO: Fast Facts" 2017). Power system operators are conservative with their use of renewable energy to ensure grid stability. ERCOT's 7-day wind forecast performances have steadily increased over the years, however the margin of error is still about 6% (Wattles 2017). With the margin of error being so large, it is safer to curtail because of the inherent uncertainties in power forecasts and as a result we see operators choosing coal over renewables because operators can reliably know how much power they will generate.

There are many ways that power forecasts represent their inherent uncertainties. Point forecasts are predictions of power generated given by one value per timestep. On the other hand, probabilistic forecasts are predictions offered as probability distribution—one for every timestep (Morales et al. 2014). Conversely, scenario forecasts present a set of values for every timestep that correspond to a set of possible outcomes. This is only three examples of power forecasts. There are so many different types of power forecasts that are developed from different statistical models.

It is difficult to determine how to schedule renewable energy generators when presented with so many different representations of the inherent uncertainties. However, the goal is for power system operators to trust intermittent power forecasts and to use them efficiently to increase the amount of renewable energy injection to the electrical grid. This study attempts to update operational practices for the purpose of encouraging renewable electrical resources. Specifically, this paper addresses the lack of a defined data model for power forecasts to help the integration of power forecasts data across many markets and operational models.

METHODS

To standardize intermittent power forecast data models, I first determined consistent definitions of characteristics of using power systems analysis and simulations to store forecasts such that power forecasts are replicable and comparable in power operation analysis. On the front of power system modeling, there are advanced operational models and analysis. By creating a constant data model the possibility of clear comparisons and reproducibility is enabled. To do this: 1) define a data model and 2) implement the data model.

A data model is defined as a simple container format used to describe and package a collection of data for the purpose of sharing between tools and people. Defining a data model requires gathering and sharing data from multiple sources for a particular data source. In particular, the model will have 5 core principles (Walsh and Pollock, n.d.). The first is that the data model is simple. Second, extensibility and customization by design—publishers may add additional metadata or constraints by adding attributes the data model. Third, it must be in a format such that is human-editable and machine-usable. Forth, the data model must be language, technology and infrastructure agnostic. Existing decision-making platforms, like MatPower and Plexos, should be able to use the data model. Finally, it should reuse existing standard formats of data (Walsh and Pollock, n.d.).

Carefully choosing a data structure in which to create the data model meets the first 4 core principles. The fields of attributes included in the data model shall be constrained to only those relevant for power system operation, making the data model simple. Additionally, I choose to write the data model in JavaScript Objection Notation (JSON). Because JSONs can be written like a dictionary, it makes it simple to add additional characteristics by adding attributes. All modern programming languages support JSON – making it interchangeable with programming languages. Moreover, JSONs are easy for humans to read and write, and easy for machines to parse and generate ("JSON" n.d.).

The last core principle—reuse of existing standard formats of data—required examining how power forecasts are being used for market operations. To meet this, requires determining how ISOs define and use power forecast attributes, as well as how researchers would define forecasts attributes when applying it to solve a common problem in power system analysis (i.e. unit commitment and economic dispatch). Unfortunately, there is ambiguity as how power forecasts are already defined.

Review Findings I: Key Attributes of Power Forecasts for Operational Practices

Over the various operational manuals and academic papers, there was inconsistent language surrounding power forecasts and how they were used. There were explicit and implicit definitions of forecast attributes. Although some papers defined how they used power forecasts and what the power forecasts they used looked like, others would just mention that a power forecasts was used. Many operational manuals would not request forecasts to be given in a certain format. Additionally, there were ambiguous definitions between researchers and system operators. The important attributes differed based on whom was speaking.

Forecasts can be categorized by horizon and their subsequent function. A short-term forecasts have horizons that range from one to six hours (Larson et al. 2016). These horizons are helpful for effective operations planning. Medium-term forecasts, instead, look ahead a day or on the timescale of days. These horizons are necessary for good management and maintenance in scheduling the system (Xie et al. 2011). They are also used for unit commitment and economic dispatch (Larson et al. 2016). In contrast, long-term forecasts are essential for investment planning in generation capacity and have horizons on the timescale of months to years (Xie et al. 2011). These functions are broad and ambiguous.

It was clear that there were two different spheres of rhetoric around power forecasts; an academic sphere and a system operators sphere. In academia, there are many important characteristics that would be considered as attributes. For example, the statistical method used to create the power forecast as it speaks to the performance of the power forecast. For the same reason the variance and the average mean error are interesting. Academic papers also suggest that the calibration and sharpness of a probabilistic power model should be considered (Botterud et al. 2013). On the other hand, aside from the actual forecasted values, systems operations only require knowing the horizon, resolution, and interval of the power forecast to use it for daily operational practices.

Although there are only three relevant terms, the definitions varied across and between academia and system operators. For example, the concentration of predictions is defined as sharpness by statisticians and as resolution by some system operators (Gneiting Tilmann et al. 2007). Antonanzas et al. (2016) and Kaur et al. (2016) denotes resolution as “the frequency at which the forecasts are issued,” while Monterio et al. denotes the resolution as the time step. For this reason, the three attributes for our data model must be explicitly defined. The forecast horizon, also known as the “look ahead time,” is the time between the first time predicted and the end of the last time predicted (Kaur et al. 2016, Antonanzas et al. 2016). The forecast resolution is the number of predictions within a time range (Kaur et al. 2016, Antonanzas et al. 2016). Last, the forecast interval is the amount of time between predictions or the discrete timesteps (Kaur et al. 2016, Antonanzas et al. 2016).

Data Model Structure Example

Power system operators need only the forecast horizon, forecast resolution, forecast interval, and the forecast data to run daily operations. Therefore, the data structures below are suggestions of how a JSON data model might look like for power forecast data for the objective of solving an economic dispatch problem. For examples of what solving the economic dispatch might look like, see the next section. Note that the data included in the examples below have randomly generated data and hold no truth for power generation levels or fluctuations. As defined above, the forecast horizon is the time between the first time predicted and the end of the last time predicted (Kaur et al. 2016, Antonanzas et al. 2016). The forecast resolution is the number of predictions within a time range (Kaur et al. 2016, Antonanzas et al. 2016). The forecast interval is the amount of time between predictions or the discrete timesteps (Kaur et al. 2016, Antonanzas et al. 2016). Additionally, there are 3 examples of the data models—corresponding to point, scenario, and probabilistic forecasts.

Power Point Forecast Data Structure for Economic Dispatch with Random Data


```
[
  {
    "type": "point",
    "horizon": 65,
    "interval": 5,
    "resolution": 13,
    "time_units": "min",
    "data": [
      {
        "timestamp": "2016-09-02T15:33:50+00:00",
        "forecast": [
          875,
          911,
          3,
          876,
          682,
          713,
          15,
          100,
          397,
          844,
          828,
          343,
          396
        ]
      }
    ]
  }
]
```


Power Scenario Forecast Data Structure for Economic Dispatch with Random Data


```
[
  {
    "type": "scenario",
    "horizon": 65,
    "interval": 5,
    "resolution": 13,
    "time_units": "min",
    "data": [
      {
        "timestamp": "2014-08-19T17:55:21+00:00",
        "forecast_s1": [
          113,
          515,
          940,
          582,
          710,
          116,
          664,
          426,
          781,
          792,
          268,
          81,
          310
        ],
        "forecast_s2": [
          320,
          640,
          83,
          783,
          412,
          935,
          852,
          379,
          126,
          191,
          343,
          969,
          916
        ],
        "forecast_s3": [
          758,
          892,
          790,
          100,
          729,
          65,
          768,
          559,
          987,
          818,
          877,
          525,
          310
        ]
      }
    ]
  }
]
```


Power Probability Forecast Data Structure for Economic Dispatch with Random Data


```
[
  {
    "type": "scenario",
    "horizon": 65,
    "interval": 5,
    "resolution": 13,
    "time_units": "min",
    "data": [
      {
        "timestamp": "2017-02-26T06:04:26+00:00",
        "quantiles": [
          "0.701",
          "0.1901",
          "0.5929",
          "0.9005",
          "0.5553",
          "0.2112",
          "0.5491",
          "0.6119",
          "0.4929",
          "0.4002",
          "0.9664",
          "0.1867",
          "0.3693"
        ],
        "forecast_q1": [
          441,
          278,
          579,
          989,
          711,
          570,
          911,
          421,
          134,
          846,
          388,
          460,
          838
        ]
      }
    ]
  }
]
```

Review Findings II: Key Attributes of Power Forecasts for Operational Practices

As part of my deep literary drive, I also noticed other types of attributes that might be beneficial to include within my data model.

Solar and Wind Power Forecasts Data Attributes

The forecast horizon can also be generalized by the type of resource being forecasted. Solar power forecasts are characterized as a short-term forecast. Trading solar power in electricity markets require looking ahead from 5 minutes to 1 hour ahead (Rana et al. 2016). A concentrated solar power station requires a day-ahead 2-day persistence forecast (Kraas et al. 2013). However, ERCOT requires PhotoVoltaic (PV) generation resources with a short-term PV power forecast as hourly forecasts for the next week (168 hours). The forecasted hours are updated as they fall within the 168-hour rolling window ("Current Operating Plan Practices By QSE" 2017). Solar PV also call for smaller forecast intervals within the given horizon (Golestaneh et al. 2016). Solar PV and concentrated solar power have different fluctuations in their output due to the changes in weather and differences in technology. Fluctuations in power flow impacts the power quality, generation-load balance, and regulation cost.

Similarly, wind power forecasts can be characterized by their horizon. A strong case study for using wind power forecasts is ERCOT—who, in July 2017, reported a 20% wind generation capacity. ERCOT requests wind power forecasts of the hourly production potential from all wind-power in ERCOT for the next 48 hours (Hui et al. 2012). Because wind power largely depends on wind speeds that fluctuate on the order of magnitude of days, medium-term forecasts are common when reporting wind power.

Market Operations Specific Data Attributes

Energy imbalance markets, as mentioned in the background, operate at 15 and 5-minute time intervals and require solving economic dispatch. Kaur et al. (2016) solves economical dispatch with power forecasts. For the 15-minute market, the power forecasts had a horizon of 4.5

hours of 18 predictions that are 15 minutes apart. The 5-minute market used a forecast that looked ahead 65 minutes with a resolution of 13 predictions at intervals of 5 minutes. During real-time operations, security constrained economic dispatch is dispatched normally every 5 minutes with a look ahead of 4 hours (Hui et al. 2012, Wang et al. 2016).

Likewise, when setting the operating reserve in the daily market operators often have to solve unit commitment. Power forecasts used to solve unit commitment more commonly have a longer horizon (Wang et al. 2011). System operators have a particular timeline they must follow to ensure reliant and resilient power flow. Therefore, they typically ask for forecasts with 24-hour horizons with a power prediction at every hour (Xie et al. 2011, Matos and Bessa 2011b). In Spain, the day-ahead market participation requires a forecast for the next day in hourly resolution (Kraas et al. 2013). Day-ahead predictability with unit commitment utilizes forecasts that look 24 to 36 hours ahead and updated every 6 hours (Xie et al. 2011).

Limitations and future directions

Unfortunately, a data model is hard to implement in practice. The absence of a data model structure to share and compare power forecast models and analysis methods spurred this paper. It is unknown now difficult or what push back the proposed data model structure will encounter. The electrical power systems industry is an established institution with policies and regulations that have been in place for a very long time. There has to be many changes to policies in place at the utility level as well as on the national level. Ideally the data model would be taken to independent system operators, who would then implement and regulate the use of a data model for power forecasts by individual utilities.

Future work must be done to show how comparisons between power forecast can be made using this structure. Thus, system operators can know how to compare and define a "good" forecast. Essentially there calls for a method to quantify the risk of trusting a power forecast and subsequently how to interrupt them such that system operators can choose more renewable energy generation. If we are able to implement the data structure, then it is possible to bridge the two spheres, academia and system operators.

Conclusion

It is difficult for system operators to integrate the many different types of power forecasts into systems operations because of the different representations of their inherent uncertainties. System operators do not know how to integrate the inherent uncertainties and are unable to assess the risk reliably with the operation practices that are currently in place. The first step to changing that needs to be making it easy to compare and replicate results throughout the field. Standardization of power forecast lingo in definitions prevalent in the power system operation sphere will bridge the academic sphere and the system operations sphere to allow the integration of advanced operational models in operation practices.

Bridging spheres would allow independent system operators to share analysis practices. For example, CaISO could start learning from ERCOT's experiences from integrating high percentage of wind power. The opening up and increasing communication between academia and practice would allow the integration of advanced operational models. As a result, independent system operators would start using power forecasts that are more accurate representations of their inherent uncertainty, such as a quasi-quantile forecast.

Ultimately, the data model would encourage system operators to choose renewable energy generation over coal or natural gas. As mentioned above, we are seeing curtailments of renewable electricity generation because system operators do not trust power forecasts ("ERCOT Quick Facts" 2017). Creating a standard data model structure for power forecasts allows power forecasts and analysis methods to be shared between research and practice (Walsh and Pollock n.d.). Thereby allowing research to be easily replicable and integrate-able into system operations, system operators will be able to identify how a paper's results could lead to better, more reliable analysis for setting generator levels.

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