Digital Transformation in Renewable Energy: Use Cases and Experiences from a Nordic Power Producer

Liyuan Xing, Gleb Sizov, and Odd Erik Gundersen

Abstract The electric power system is changing. The changes include the integration of renewable resources, such as wind farms and solar plants, making the grid smarter so that it can react and adapt to changes and increase customer engagement. These changes of the power system have radical effects, which can only be tackled if it is digitized, so digital transformation of the power system is of paramount concern.

Electrical energy management systems are therefore an integral part of the digitization process. Such systems typically provide the fundamental information and computation capability to perform real-time network analyses, to provide strategies for controlling system energy flows, and to determine the most economical mix of power generation, consumption, and trades. Currently, the maturity of digitization is at different levels for various parts of the electrical power system. Machine learning has been suggested as a tool for making smart grids that can adapt to sudden changes and long-term distributional shifts and recover from errors. The interest in implementing machine learning methods into energy management systems has grown in recent years, and many companies are taking the first steps.

TrønderEnergi is a Norwegian power generation company that does exactly this. It aims at increasing the value of renewable energy and at the same time reducing the cost. In the context of hydropower and wind power, there are several use cases that undergo digital transformation in TrønderEnergi. Examples of such use cases are (1) hydropower trading, (2) wind power trading, and (3) predictive maintenance on wind farms and hydro plants. These use cases as well as the digital transformation processes are introduced in detail in this chapter along with our practical experience. We discuss how machine learning helps to improve the functioning of the existing

L. Xing (✉) · O. E. Gundersen
Norwegian Open AI Lab, Norwegian University of Science and Technology, Trondheim, Norway

TrønderEnergi Kraft AS, Trondheim, Norway
e-mail: liyuan.xing@tronderenergi.no; odderik.gundersen@tronderenergi.no

G. Sizov
TrønderEnergi Kraft AS, Trondheim, Norway
e-mail: gleb.sizov@tronderenergi.no

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systems and optimize operations. Inspired by these use cases, we believe digital transformation will continue to make inroads in other applied areas in energy management systems and form the digital electric power ecosystem.

1 Introduction

1.1 Current and Future Electric Power Systems

An electric power system (EPS) is a network of electrical components deployed to supply, transfer, and use electric power [1]. A typical example of an EPS is the electrical grid that provides power to homes and industries within an extended area. The electrical grid can be broadly divided into the generators that supply the power, the transmission system that carries the power from the generating centers to the load centers, and the distribution system that feeds the power to nearby homes and industries.

The structure of future EPSs may be represented in an aggregate form as a three-level super-mini-micro system (see Fig. 1 in [2]). In Norway, the structure is mainly super grid with large hydro and wind renewable energy resources, mini grid with many small hydro plants connected to a distribution network, as well as micro grid with micro hydropower plants, batteries, and electric vehicle charging.

Renewable energy flows through Norway as summarized in [3]. Specifically, Norway is the seventh largest hydropower nation in the world and the largest in Europe. Moreover, developments of both onshore wind and floating offshore wind have come fast. Fosen wind is realizing Europe's largest onshore wind power project in Central Norway. Equinor (Norwegian state-owned multinational energy

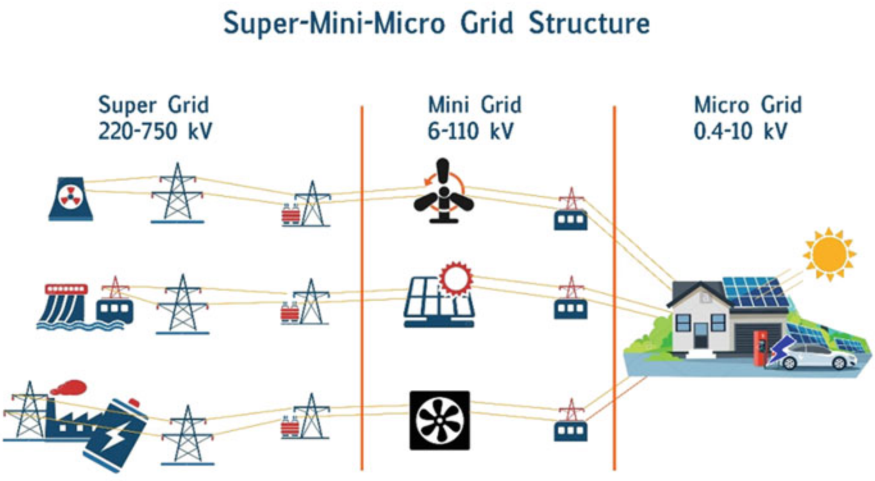

Fig. 1 Three-level super-mini-micro EPS, from [2]

company) is currently the world's leading floating offshore wind developer. In October 2017, the company opened Hywind Scotland, the world's first floating offshore wind farm. Large-scale energy storage could hold one of the keys to the successful scaling of renewable energy production. To this end, the Norwegian company Ruden has developed an "underground electric battery" in existing geological structures.

Globally [4], hydropower accounts for 54% of the renewable power generation capacity, and wind energy is the second largest renewable energy after hydropower which accounts for approximately 24%. As mentioned in [5], Norway has endorsed the EU Renewable Directive and has plans to increase its renewable energy ratio from 58.2% in 2005 to 67.5% by 2020. As of 2020 [6], 1690 hydropower plants account for 88% of the Norwegian electricity production capacity while 53 wind farms account for 10%. However, wind power is currently the dominating for of investment. Due to the latest controversy in wind farms on land in Norway, the general expectation is that the growth in wind power will come from offshore wind farms.

With renewable electricity at the supply side of the upstream for the zero or minimal greenhouse gas emissions and sustainable developments, the same holds true on the downstream where consumers become more sustainable by adapting to variability of the renewable energy sources. Norway is the electric vehicle capital of the world, as reported in [7]. Specifically in 2020, 74% (54% fully electric cars and 20% plug-in hybrids cars) of the new cars that were sold in Norway were electric vehicles. The political goal is for all new car sales in Norway to be zero emission (electric or hydrogen) by 2025. Moreover, customers are increasingly valuing services that use digital technology (e.g., smart homes, office buildings, supermarkets) for energy savings. Intelligent demand will be an increasingly important dispatchable resource. In this way, customers are more engaged in energy supply and demand, as pointed in [8].

Sensors and information technology are increasingly permeating the distribution power system (middle part of Fig. 1) [7]. For example, the regulators in Norway have already required to implement smart meters by 2019-01-01, as cited in [9]. In addition, 7.4% of hydropower came from distributed small-scale hydroelectric power plants (SSH) in the middle grid in 2017 [5]. There is an increasing interdependence of information technology and energy technology, with smarter grids opening pathways to greater functionality (e.g., situational awareness) and active management of more diverse sets of resources providing a range of services that can be monetized in energy markets [8].

Yet the pathway to electric power system evolution is highly sensitive to each local situation and its technical, economic, and political factors. Among many others [8], the three main and fundamental trends, including renewable resources integration, smart grid, and customer engagement as aforementioned, have driven the electric power system evolution in Norway.

1.2 Challenges and Opportunities for Energy Management Systems

Radically evolving power systems and rapidly developing technology bring a unique set of challenges and opportunities for the EMS (as defined in [10]) to monitor, control, and optimize the performance of the generation and transmission systems, adding value through computer-aided tools.

The perpetual task in EPS is balancing energy production and consumption. It means that the amount of electricity fed into the electricity grid must always be equal to the amount of electricity consumed; otherwise, there's a blackout which is a total crash of the power grid. Therefore, multiple parties (high-voltage transmission system operator (TSO), access responsible parties (ARPs), producers of electricity, and large consumers) are involved in managing the balance on the grid. Moreover, several energy markets are designed to incentivize producers to provide accurate power production forecasts and help to balance the power system. Specifically, wind power producers participate in the physical market by nominating production forecasts to spot/day-ahead market (12–36 h ahead), trading on the intraday market (usually 1–8 h ahead), and providing re-planning forecasts (45 min ahead) in the balancing market.

Integration of renewable energy sources is one of the main challenges in EPS right now. Renewable energy sources such as solar and wind power depend on weather conditions, which cannot be controlled or predicted accurately. This makes the balancing task more challenging. This challenge can be addressed from different perspectives. From infrastructure viewpoint, more storage can be integrated so that overproduction or overconsumption can be compensated by charging/discharging the storage. From software viewpoint, algorithms for power production and consumption forecasts, as well as automatic bidding and trading in various markets, can reduce the imbalances.

There is increased energy efficiency in the value chain to save cost and reduce environmental impact in both power generation and consumption. Customer engagement becomes more economically feasible and socially acceptable, as one of the trends [8]. Therefore, the rest of the power sector faces the challenge of keeping up and embracing the need to co-optimize electricity supply and demand dynamically. It includes treating largely inelastic demand as a fixed target during planning, regulation and market design, and meeting the demand by building a dispatchable supply stack with utilities and grid operators.

With the increased complexity and risk of the more intermittent and less predictable renewable energy sources, largely inelastic demand, finer time resolution (moving from 1 h to 15 min) for trading, and settlement in Nordic energy markets [11], it is impossible to rely on manual human actions or conventional energy management systems that cannot adapt to the complex market situations based on vast amount of data.

With increased availability of sensor, market, and operational data, as well as the advanced information technologies, there is an opportunity to automate operations in electric power ecosystem to take actions with less human intervention based on continuous check of the system states in a much more detail manner than it was before. Sophisticated computer tools are now the primary tools in solving difficult autonomous decision-making problems that arise in the areas of power system planning, operation, diagnosis, and design. Among these computer tools, machine learning (ML) has grown predominantly in recent years and has been applied to various areas of power systems.

ML is the study of computer algorithms that improve automatically through experience and using data [12]. ML algorithms build a model based on sample data, known as "training data," to make predictions or decisions without being explicitly programmed to do so. Therefore, they are used in a wide variety of applications where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

1.3 Digitization Maturity Levels

Basically, electric power system is a typical example of industrial internet of things (IIoT) [13], which refers to interconnected sensors, instruments, and other devices networked together with computers' industrial applications for better addressing fluctuations in production, demand, and pricing, adjusting bid and trade in energy markets, dispatching resources, planning predictive maintenance, as well as maximizing economic benefits.

Most electric power companies already have many digital solutions for energy management in place, but the digitization stays at different maturity levels for various applied areas of power system. Measuring and evaluation of the digitization levels in structured way can make digital transformation process easier to implement. The IoT pyramid [14] represents successive stages of digitization and also serves as a reference framework for the maturity assessment. In the pyramid, there are five stages from bottom to top as follows, where implementation of the top ones is more difficult and requires the ones below to be implemented first.

Connectivity: Collect/provide relevant data through vertical and horizontal integration.
Information: Derive data from information and create transparency.
Knowledge: Make knowledge explicit and provide it as per requirements.
Forecast: Detect patterns and use them for forecast.
Autonomy: Autonomous system decisions.

We try to explain and concretize these five stages with (a) traffic lights example from [15] and (b) another example of predictive maintenance for wind turbines in the energy domain.

Connectivity: Data are facts, symbols, and signals about who, what, when, and where. For example, (a) red is a signal of traffic lights; (b) vibration amplitude is an important sensor signal for wind turbines.

Information: Information has meaning by linking who, what, when, and where to describe a situation or event. For example, (a) the south facing traffic light on the corner of Pitt and George Streets has turned red; (b) vibration amplitude from a certain component (e.g., bearing) of a wind turbine.

Knowledge: Knowledge has context and provides insights and understanding of something. For example, (a) the traffic light I am driving toward has turned red; (b) check the frequency range of the vibration to identify the defect in a bearing.

Forecast: Predict what is going to happen in the future. For example, (a) the traffic light is going to be green in a minute; (b) forecasting the remaining useful life of the defected component.

Autonomy: It places knowledge and forecast into a framework that allows them to be applied for making decisions. For example, (a) I had better stop the car now but can drive in a minute! (b) preparing and planning the maintenance in advance to avoid unnecessary downtime.

1.4 Present Situation in TrønderEnergi Norway

TrønderEnergi [16] is a Norwegian national player with Nordic ambitions for the next-generation energy management. As a purebred energy company, we deliver the state-of-the-art renewable energy solutions and services of the future, building upon our 70 years of industry experience on hydropower. The company is trying to lead the way in the evolution of the electric power system that is happening in Norway.

TrønderEnergi is a major player in renewable energy for a better society (zero CO_2 emissions). We produce both hydropower and wind power. In 2020, the company had the proportion of hydro and wind around 80/20 (2.4 TWh/0.6 TWh), with the plan to reach 38/62 (2.4 TWh/3.9 TWh) in 2025 and 30/70 (2.4 TWh/5.4 TWh) in 2030. The strategy is to become one of the most profitable hydropower producers in Norway and a leading Nordic player in wind power.

TrønderEnergi is also responsible for power trading and innovation in renewable energy. Through market activities, the company positions itself to use the opportunities in new renewable technologies, new business models, and new market models for the power industry.

TrønderEnergi has contributed to establishing Norway's second largest grid company. It holds the ownership in one of Norway's largest grid companies but also moves toward the downstream business and is taking a position in the continued electrification, through partner-based growth in energy services with Ohmia Retail, Ohmia Charging, and Ohmia Construction.

Different from most energy companies, TrønderEnergi employs an inhouse AI department since 2018, counting more than ten ML engineers. Based on the company's digital platform, their main responsibility is to further provide the innovative, reliable, and robust AI energy services for both TrønderEnergi and third parties. Among the different digital transformation enablers, which are technology, organization, and process, the main driving force in TrønderEnergi is coming from organization.

Depending on the application areas, the maturity levels of digitization are in different stages. The AI team facilitates the digital transformation from its current maturity levels toward forecasting and autonomy, as defined in the IoT pyramid, using optimization and decision-making techniques, not limited to ML. The AI department has been working on many key areas in TrønderEnergi from the upstream of hydropower and wind power production forecasting, planning, trading, and maintenance, through the middle stream of power transmission with grid loss estimation [17], to the downstream of power consumption and flexibility. Among these, we are going to introduce in detail upstream use cases from hydropower and wind power trading and predictive maintenance.

1. **Hydropower trading:** transformation from forecast to autonomy
2. **Wind power trading:** transformation from forecast to autonomy
3. **Predictive maintenance:** on wind farms and hydro plants, transformation from knowledge to forecast

1.5 The Changes in Digital Transformation

Digital transformation is the process of using digital technologies to create new—or modify existing—business processes, culture, and customer experiences to meet changing business and market requirements [18]. This reimagining of business in the digital age is digital transformation. The two distinctive characteristics of digital transformation are (1) (re)defining an organization's value proposition and emergence of a new organizational identity [19, 20] and (2) changing the ways people work, thereby affecting the operations, culture, and experiences [21].

Regarding the first point, by automating wind power trading and predictive maintenance, TrønderEnergi is expected to offer a complete range of wind farm management services. The new integrated service across the value chain is key to optimal long-term profitability of the managed assets. Moreover, it enables the scaling of existing services through automation, providing energy management for more assets with less manual inspections, meaning higher efficiency with fewer people. It enables TrønderEnergi not only to manage its own wind farms but become a service provider for operating wind farms belonging to other companies. It changes the business models and adds more values, making TrønderEnergi a leading Nordic wind farm operator.

Regarding the second point, it correspondingly changes how people work. After automating the tasks in the new value chain, manual tasks become limited to monitoring and interventions for rare events that are not reflected in the data and require deep domain knowledge and skills to be handled. This change reduces the amount of work but maintains the demand for domain experts that develop and supervise automation systems. It also allows for the emergence of new skills. For example, operators need to learn how to interact and interpret data and outputs from ML applications that often lack sufficient ability to explain—sometimes erroneous—predictions generated by black box ML algorithms [21].

2 Digital Transformation

2.1 Use Case Background

2.1.1 Power Markets

The Nordic electricity market consists of several markets that provide different "time windows" for trading physical power: the day-ahead market, the intraday market, and the balancing market [22]. In addition, there is a financial market, where price securing contracts are traded. These different markets with their timelines as well as type of trades and market operators are summarized and drawn in [23]. Power producers, TSOs, power-intensive industries, large consumers, and power companies actively participating in the power markets are defined as power market actors.

In the Nordic countries, most of the trading is done on the day-ahead market (spot market), where a daily competitive auction establishes a price for each hour of the next day, called spot price. It is calculated after all participants' bids have been received before gate closure at 12:00. Participants' bids consist of price and an hourly volume in a certain bidding area. Retailers bid in with expected consumption, while the generators bid in with their production capacity and their associated production costs. The spot price is determined as the intersection between the aggregated curves for demand and supply for each hour—taking the restriction imposed by transmission lines into account. It is crucial for price formation within the other time windows, i.e., the intraday and balancing markets and the financial market for long-term contracts.

The intraday market is primarily a correction market, where actors can trade their imbalance, including adjusting any earlier trading if the forecasts turn out to be wrong. Over the years, lead times for intraday trading have gotten shorter, while traded volumes have gotten larger, caused by increased feed-in from fluctuating energy sources. While day-ahead trades are related to market clearing price principles, where the last accepted bid sets the price for all transactions, the prices in intraday trading are set in a "pay-as-bid" process [24], based on a first-come, first-served principle, where best prices come first—highest buy price and lowest sell price. This means prices are assessed in continuous trading based on each transaction that is completed. Therefore, bid prices are often used in intraday trading. The result is that there are no fixed prices for products on the intraday market. Moreover, the intraday bid can be done up to 1 h before the delivery hour and can trade in multiple products (hours). Both the day-ahead market and the intraday market are operated by

Nord Pool that merges bids on the day-ahead spot market (Elspot) and intraday market (Elbas) and publishes the result on their website.

The balancing market is trading automatic and manual reserves used by the Nordic transmission system operators (TSOs) to maintain power balance during the operation hour. The bidding can be updated up to 45 min before the delivery hour, and bids are called in real time by TSOs if the regulation is needed. The last activated bid in the operating hour will determine the price of the balancing power (regulation price) at this hour. When an upregulation takes place, the most expensive bid that has been activated will determine the regulation price for all the called bids, while downregulation takes the cheapest activated bid for regulation price instead. Moreover, in Norway, Statnett has been using a two-price system to price imbalances from the power producers, so that any deviation in the power production in the opposite direction to the regulation direction will be penalized. However, from November 2021 [25], the two-price system is transitioned to the one-price system which removes the possibility to reduce the imbalance by updating a short-term forecast 45 (replan). The main ways to reduce imbalance and consequently costs are to make the day-ahead forecasts more accurate and trade the imbalance volumes on the intraday market.

Financial power markets operate like other derivative trading markets. Trading in these markets has been drawing a lot of attention for decades and is a broad field, not specific to hydropower and wind power trading. Therefore, our focus will be on the daily bidding in the short-term markets.

2.1.2 Digitization Stages

According to digitization levels defined in Sect. 1.3, all three use cases in TrønderEnergi have already been implemented for the first three levels, as summarized as follows:

Connectivity: related sensors installed and connected to a data acquisition system.
Information: data is aggregated and stored in a centralized data platform SCADA.
Knowledge: data is processed, analyzed, and visualized in reports and dashboards available to operators, technicians, analysts, and managers.

Thereafter, TrønderEnergi inhouse domain experts make use of the knowledge for further forecasting and decision-making. When going toward the top of the IOT pyramid, domain experts' knowledge is used to build forecasting and autonomous decision-making systems.

For trading, the next two levels for the digitization of trading involve:

Forecast: power production is forecasted (wind power) or planned (hydropower) using ML and optimization models.
Autonomy: based on the forecasts, the bids are generated and submitted for trading in physical power market. Interactions with the market are implemented through API calls.

For predictive maintenance [26], every breakdown of a key component can cost millions and pose a safety risk. Predictive maintenance utilizes real-time data to detect anomalies and defects and predict failures. Maintenance is important for efficient operation and to avoid unplanned downtime. If the need for maintenance is detected in advance, it can be used to optimize maintenance scheduling to decide when to stop production, order parts, and organize technicians' work to do the repairs. The next two levels for the digitization of predictive maintenance include:

Forecast: predicting the expected lifetime of key components, such as gearboxes and bushings of wind turbines

Autonomy: using the forecasts to optimize the maintenance scheduling and interact with other related systems, such as power production forecasts

2.2 Hydropower Trading

Hydropower is an extremely flexible and stable energy source. Water can be stored in reservoirs until needed, allowing for quick changes in production and low start and stop costs. Well-regulated reservoirs can provide short-term flexibility within an hour, as well as long-term flexibility over days, weeks, and seasons. Therefore, hydropower planning takes long-term water value into account when optimizing the short-term production used for generating bids. It means deciding whether to use available water right now or wait and sell in future hours to maximize profits, which is different from nonflexible and intermittent power sources like wind and solar.

Hydropower is the main source of electricity in Norway with a long history; there are common third-party optimization and automation tools available that can be used for daily day-ahead and hourly intraday planning and trading. Take SHOP [27], for example; it is a modeling tool for short-term hydro operation planning, where the optimized production for the next day is closely related to the bidding in the day-ahead market. Moreover, work process (consisting of several steps by SHOP) can be standardized in Powel Nimbus [28] for production planning and backed trading. Volue Algo Trader [29] is another example; it allows implementation of trading strategies that automatically submit bids to the intraday market. Nowadays, all the trading operations are executed using digital platforms integrated with the corresponding markets through API calls.

With the support of these tools, domain experts are often involved in generating and updating the bids, which are submitted either manually or automatically. For example, TrønderEnergi has several inhouse operators who check and sometimes adjust bids for the short-term markets, after they are generated by automation tools such as SHOP. It makes the trading process semi-automatic and dependent on the domain experts' experience.

2.2.1 Current State

TrønderEnergi, as a hydropower producer, participates in all four markets mentioned in Sect. 2.1. According to the digitization stages described in Sect. 1.3, hydropower trading operates at the stage of partial autonomy—stage 5; especially day-ahead trading is at the highest stage when compared to intraday and balancing trading.

Day-ahead bid is the expected amount of supply at different prices for hydropower the next day. They are sent to the day-ahead energy market Nord Pool before noon every day. The bid is a matrix of price-quantity pairs for each hour of the following operating day, starting at midnight. The market is cleared once every day, and producers are notified of their obligations. Market commitments become known after the spot price is released; producers have the option of re-optimizing the production schedules in order to cover the load with minimum costs.

The Nordic countries deregulated their power markets in the early 1990s, and the day-ahead bidding methods are relatively mature. There are several existing standard bidding methods [29] for hourly bids. These bid methods are based on:

(a) Expected value—bid the optimal volume price independently, given expected price and inflow.
(b) Marginal cost—long-term water value is transformed into cost by using turbine efficiency; bid the marginal cost giving a price-dependent bid which is equal for each hour.
(c) Multi-scenario deterministic—run a lot of price scenarios and find optimal production and then combine them together.
(d) Stochastic optimization—explicitly optimize the bid given a discrete distribution of price and optionally inflow.

Most of the power generation companies in Nordic, including TrønderEnergi, are using the marginal cost-based bidding methods. In TrønderEnergi, it is done by first running optimization with SHOP [27] and then manual processing in Excel. The manual processing includes adjusting the water value from the long-term model due to its weaknesses and to get a better production scenario with fewer stops.

A challenge for multi-scenario deterministic bidding is the crossing price profiles by multiple separate SHOP runs, so a general stochastic hydropower optimization is formulated with uncertain price and inflow. Extra restrictions are added in the bidding period to ensure a well-behaved multi-scenario approach without any crossing price profiles. This stochastic short-term model SHARM [30] is developed and implemented by SINTEF. To the best of our knowledge, it has not yet been used by any Norwegian hydropower company for the day-ahead bidding because of the crucial details left to be solved for implementing it in practice.

As seen from the previous description, the day-ahead bidding is with many manual inputs and multiple SHOP runs for adjustments by the operators. However, there is still room for improving bidding to maximize profit from day-ahead market and automating the process so that the operators can shift their focus from making bids to choosing among the alternatives suggested by the system.

As for bidding in intraday market and balancing market, the time resolution and bidding horizon become smaller (15 min from 2023 [11]) compared to day-ahead market. It will be impossible to generate optimal bids manually for such short intervals. With 1-h interval, the operators try to trade the imbalance at least once a day, sometimes several times per hour, which is still far away from the allowed time resolution that allows for more frequent bid updates based on more recent and accurate information obtained in stage 2.

Specifically, there are three processes included for hydropower handling post spot to trade the imbalance; they are (a) trading in the intraday market for profit; (b) bidding into the balancing market; and (c) renominating in the balancing market to benefit from the single-price imbalance cost as opposed to the two-price imbalance cost (becomes irrelevant from November 2021 [24]).

In TrønderEnergi for hydropower, so far, all these imbalance processes are performed semi-automatically and involve manual works from the operators. For example, (a) intraday trading itself is performed manually, but cost and volume blocks come from automatic processes; (b) bidding in the balancing market is set up manually once per 24 h, and then bids are updated automatically as production schedule changes (for instance, due to an intraday trade); and (c) sending updated nomination data is done either manually or automatically, following an intraday trade.

Therefore, the next step in digital transformation is more automation in scheduling using the latest available information for better prediction and bidding to enable continuous process for trading in intraday and balancing markets at finer time resolution.

2.2.2 Next Steps

The goal with improving the bidding process in the day-ahead market is not only to increase profit but also to reduce the manual work required by the operators. The intention is to fully automate the bidding process. To improve bids, we need to take more uncertainty about the price and inflow forecasts into consideration. To accomplish this, we are moving from deterministic optimization with SHOP to stochastic optimization with SHARM. In addition, operators do not need to manually adjust the water value to get fewer stops as aforementioned, because SHARM takes the probabilities of different load scenarios into account and calculates bids that give the expected highest profit. One of the key points in this transition is to replace the operators' "gut feeling" adjustment for fewer stops with a quantitative method provided by SHARM.

SHARM is a stochastic version of SHOP; it has functionality to determine the optimal bid volumes using a set of discrete scenarios with probabilities for spot price and inflow. In the current SHARM bid, all prices in the bidding period from price scenarios are used as bid prices, and linear interpolation is used where there is no explicit production point; bid matrix is reduced if there are too many points [31].

It might seem that bids generated by SHARM are ready for use, but the reality is that there are crucial details left to be solved to use it practice. On the input side, the selection of bid prices is crucial, and the price scenarios should have a good coverage of extreme low and high prices; meanwhile, they should not miss prices near water value. On the output side, the bid should preserve the production jumps and must run production from the plants by having the stair bid, not always interpolating linearly.

Different from the stochastic optimization SHARM approach, there is research about hydropower optimization using deep learning [32]. Applying deep reinforcement learning and transformers for hydropower planning and bid generation is still in the early experimental stage.

When compared to bidding for day-ahead market, bidding for intraday market is less mature. There is less hydropower imbalance to trade because hydro is flexible and stable. Still, a small amount of imbalance can come from inaccurate pricing and inflow forecasts, incorrect input constraints, and conditions used in production planning. Simple intraday bidding strategies are developed based on spot prices and bids available in the intraday market. More advanced intraday bidding strategies include regulation price forecasts and different preferred risks. However, unlike spot price forecasts offered by many third providers, accurate regulation price forecasts are harder to come by. Relevant data from both the real world and various markets should be collected to predict the regulation price. Moreover, trading strategies with different risks should be allowed for selection, generating the corresponding bids for automatic submission and trading. Further details will be introduced in Sect. 2.3.1 for wind power trading, where intraday trading is more essential.

If the imbalance is not traded in the intraday market, it still can be handled in the balancing market. However, without submission of either intraday or balancing power bids that use the latest information, the deviation of power production might be in the opposite direction from the regulation direction, which will be penalized by additional cost. For the balancing market, because of the transition from two-price to one-price system, the increased focus is placed on trading forecasted imbalance on the intraday market, instead of balancing market.

2.2.3 End Goal

Even with all the processes mentioned in the previous section implemented, there is still work left for the operators that requires a lot of knowledge and experience, for example, adjusting the water values from the long-term model for generating the day-ahead bids and selecting suitable trading strategy and risk parameters for generating the intraday bids. These adjustments originate from errors in the forecasts, which cannot be eliminated because of the uncertainty in future conditions and events. Therefore, better handling of uncertainty in time series forecasting (e.g., prices, inflows, water values) will further improve the bidding performance and reduce human intervention and eventually result in higher autonomy.

Probabilistic forecasts capture uncertainty by predicting a distribution over a range of values. A prediction interval gives a range of values the random variable could take with relatively high probability. For example, a 95% prediction interval contains a range of values which should include the actual future value with probability 95%. Quantiles are a generalization of prediction intervals without making assumptions about the distribution. Many ML methods can predict quantiles by using quantile loss [33], such as linear quantile regression, neural networks, and gradient boosting.

By modeling uncertainty of price scenarios, inflow, and water values more accurately, the SHARM bids can perform even better, and less manual adjustment from operators will be needed. With explicit modeling of uncertainty for the regulation price, it can be used in bidding strategies with preferred risk by selecting different quantiles. Operators and decision-makers will be able to adjust the corresponding risk when they notice special situations based on the information from other sources. Therefore, better bidding and more autonomy in trading can be achieved with better handling of uncertainty.

2.3 Wind Power Trading

Wind power is a nonflexible and highly variable source of energy. The amount of energy produced mostly depends on the wind conditions that can change rapidly. An unforeseen increase or decrease in production creates an imbalance in the market. In addition, increased production can cause congestion in the electric grid. As mentioned in Sect. 1.2, effective integration of wind power into EPS is one of the main challenges the energy industry has right now.

Wind power is traded in the same physical energy market as other energy sources; see Sect. 2.1.1. These markets incentivize accurate power production forecasts to help balance the market. For wind power, the focus is on short-term forecasts, from 10 min to 36 h ahead. The forecast accuracy improves when more recent information is considered. Therefore, to maximize profits, the forecasts are updated frequently, e.g., every 10 min, and forecast imbalance, the difference between the previous and the most recent forecast, is traded in the intraday market. Effective intraday trading involves short-term forecasting of a regulation price, which is the price of electricity paid for the remaining forecast imbalance, after day-ahead nomination and intraday trading.

Control over wind power production is limited to reducing the amount of energy produced, so-called curtailment, used in case of grid congestion and special weather conditions and during maintenance of wind turbines. Long-term planning for wind production is used to plan maintenance, choosing time periods where electricity prices are low. This is different from hydropower with large integrated storage, where long-term production planning is the essential part of the operation to maximize profits from trading in the energy market.

2.3.1 Current State

Wind power trading in TrønderEnergi is automated, including data gathering, data processing, forecasting, and trading. Human involvement is limited to monitoring and interventions to handle rare events that are not reflected in the data. According to the IoT pyramid described in Sect. 1.3, wind power trading is mostly autonomous—stage 5.

An important part of reaching this stage is integration between systems, from sensors installed in wind turbines to market APIs. Several vendors provide systems for integration and automation of the processes involved. TrønderEnergi adapted these systems for day-to-day operations and now focuses on improving algorithms for forecasting and decision-making, stages 4 and 5.

As already mentioned, forecasting wind power production and prices benefits the most from advances in data engineering and ML. Making the data usable for applying ML models is a major part of automating and improving wind power forecasting. For instance, when preprocessing the data, it is important to account for curtailment, e.g., maintenance when power production is reduced or grid congestion. Technical problems in communication infrastructure or external APIs may result in missing or stale data. Power production can also be reduced because of icing. No matter what happens, the forecasting system should be able to generate forecasts, albeit the accuracy of these forecasts might be reduced. Cleaning the data influenced by external factors is also essential to maintain accuracy.

Wind power forecasting is a time series forecasting problem with covariates that capture weather conditions such as wind speed and direction. In theory, the power curve [34] provided by wind turbine manufacturer that indicates how large the electrical power output will be for the turbine at different wind speeds can be used in combination with the weather forecast. In practice, though, the power curve provides poor forecasts of how much power will be produced. Other factors, such the landscape around individual turbines, their location within the park, and wear of turbine components, must be taken into account. Forecasting models might also partially compensate for errors in weather forecasts.

The challenge of wind power forecasting received a lot of attention. The Global Energy Forecasting Competition (GEFCom) since 2012 [35] attracted hundreds of participants worldwide, who contributed many novel ideas to the energy forecasting field, including wind power forecasting. As summarized in [36], the top 5 teams in wind power forecasting GEFCom2014 employ nonparametric approaches and mostly used machine learning models such as gradient boosting machines (GBM) and quantile regression forests (QRFs), based on large numbers of input variables and features, stacking models in multiple layers. When compared to other tracks (solar, load, and price forecasting), wind power forecasting takes the highest place in probabilistic forecasting maturity. This is largely because wind power forecasting is the closest to meteorological forecasting, where probabilistic forecasting is well-established and commonly accepted.

One of the challenges we had to address in TrønderEnergi is the cold-start problem. For new wind parks, there is little production data available, and the quality of data is inconsistent due to configuring and testing wind turbines. In TrønderEnergi, we implemented a type of transfer learning where models trained on other parks are adapted for new park [37].

Wind production forecasts enable trading of wind power in different markets. Because of different pricing mechanisms, the mechanism for trading in different markets is also different. For day-ahead market, wind production bid contains all the forecasted production at any positive price (price can be negative on rare occasions). The actual price we get for this volume is the spot price determined by Nord Pool by balancing the supply and demand. However, in the intraday market, bid prices need to be provided in addition to the imbalance volume between the day-ahead forecasts and intraday forecasts. To gain insights as to what a good bid price is, it makes sense to use an estimate of the regulation price. As such, predicting hourly regulation price for each Nord Pool system area is a key process for bidding in the intraday market.

Regulation price is related to several factors, including historical and forecasted imbalance volumes, spot prices, spot bid curves, and inflows in each Nord Pool system area. Moreover, future imbalance volumes depend on factors such as wind production and other energy sources, spot flow, and buy volumes. These factors need to be modelled for predicting the imbalance volumes and further the regulation prices.

Based on the regulation price forecast, we can determine a reasonable price for bids in the intraday market. Different strategies can be developed and operationalized using automated trading systems that interact with the market. These systems communicate with the market, continuously sending and receiving information about bids and trades. They usually provide APIs and GUIs for both automatic and manual monitoring and control of the strategies.

When compared to flexible hydropower trading where the main trades are done in day-ahead market and less in intraday market, wind power trading relies more on the intraday market because wind power lacks flexibility and is intermittent with large fluctuations. It means more trades with larger volumes are inevitable for wind power in the intraday market.

All the wind production forecasting services and bidding services are running in the cloud at a regular schedule before the deadline for different markets with the latest available information. In TrønderEnergi, market participation for wind power is automated with human involvement mostly limited to monitoring, handling of exceptional situations, and occasional data entry. According to digitization levels defined in Sect. 1.3, wind power trading in TrønderEnergi is implemented on all five levels. Since 2020, TrønderEnergi offers a complete range of wind farm management services, including wind production forecasts and trading. In 2021, TrønderEnergi is a leading Nordic wind farm operator operating 13 wind farms, including Norway's second largest wind farm—Roan wind.

2.3.2 Next Steps

There is room for improvement for each component in wind power trading including wind production forecasts, regulation price forecasts, and trading strategies. More robust and accurate models can increase autonomy and maximize the profit. Based on the analysis of the results from wind power forecasting, we see that not only ML algorithms need to be improved. Other parts of the system such as automatic methods for filtering out the dirty data need to be improved. The workflow processes of the operators may need to be re-organized to make sure the input data required by the ML algorithms is correct and updated, for example, registering availability of wind turbines. These continued improvements seem iterative and never ending.

Going from point forecasts to probability forecasts has the advantage of taking uncertainty into account. As summarized in GEFCom2014 [36], probabilistic wind power forecasting is a relatively mature field. Extension of probabilistic forecasting to regulation prices and imbalance volumes would allow us to develop different trading strategies that account for different risks.

For both point and probabilistic forecasts, the use of ML methods has grown rapidly in recent years, applied to various areas of power systems. Among ML methods for probabilistic forecasting, quantile regression is the most popular method since no assumption about probability distribution is needed. Moreover, Bayesian optimization [38] is often used to find the optimal model parameters for each predicted percentile.

To increase profitability, existing trading strategies must be analyzed, and new state-of-the-art trading strategies must be developed based on lessons learned from the existing ones and literature. Further activities can be created depending on analytical and empirical back-testing results.

Further work on transfer learning methods would be beneficial for wind power forecasting in different wind parks and imbalance volumes and regulation price forecasting in different Nord Pool bidding areas. Trading strategies might benefit from including regulation prices from different areas.

2.3.3 End Goal

Intraday trading is a key component for trading power produced by renewable energies when quickly changing weather forecasts result in an unplanned shortfall or surplus of power from solar or wind power plants. Different from the nonflexible wind power, hydropower is flexible because of the storage in the reservoirs and can be treated as a kind of control reserves. Therefore, depending on the forecasted regulation prices and marginal cost of hydropower, hydropower can be utilized to compensate for wind imbalances in addition to trading on the intraday market. To reach the end goal of maximizing profit and stability, multiple renewable resources should be integrated, and corresponding trading strategies should be developed.

Changing market dynamics because of the intermittent and distributed power production pose new requirements to energy management software system. For example, software systems should allow manual changes in the system, e.g., modify trading strategies and add new data sources. With the regulatory changes in the market such as transition to one-price system, more trades go into the intraday market than the balancing market. Supporting software systems should be able to adapt to these changes.

Software systems that involve ML should be self-adaptable to handle non-stationary distribution or shifts in data. ML models should be re-trained and selected automatically. For cold-start problem with no or little data for new wind farm or new bidding areas, transfer learning can be used to leverage old data on new assets.

2.4 Predictive Maintenance at Wind Farms and Hydro Plants

Predictive maintenance [39] is the process of constantly monitoring the condition of in-service equipment and estimating when maintenance should be performed, i.e., not too late, but not too early either. This approach promises cost savings over routine or time-based preventive maintenance because tasks are performed only when warranted.

For wind farms, the main equipment that needs to be monitored is wind turbines. Depending on the type of wind turbines, among the key components are gearboxes and bushings. The goal is to predict their expected lifetime based on the various related data gathered from the sensors, for example, raw vibration and vibration trend data, as well as real-time SCADA data for different turbine components.

For hydro plants, the equipment that needs to be monitored is rotating equipment (mostly turbines and generators), in particular, the cases [40] of rotor fault (e.g., short-circuit) detection, condition monitoring of pump drainage, generator bearings, turbine hydraulic system, transformer cooling system, and servomotor forces. The relevant data can be collected from sensors, such as vibration sensors (accelerometers), acoustic emission sensors, microphones, and so on.

2.4.1 Current State

In TrønderEnergi, all the relevant data have been gathered and saved in our centralized data platform. The domain experts have the knowledge of how to use and analyze the data for planning the maintenance. As mentioned in Sect. 2.1.2, predictive maintenance stays mainly in stage 3 according to the IoT pyramid described in Sect. 1.3. The further task is to automate the process by developing corresponding predictive maintenance algorithms that can detect anomalies and failure patterns, provide early warnings and remaining useful life, and identify main causes of failure. This will move us into stage 4. Maintenance scheduling, ordering of new parts, as well as coordination with power production forecast can be automated, which is part of stage 5.

Predictive maintenance differs from preventive maintenance [39] because it relies on the actual condition of equipment, rather than average or expected life statistics, to predict when maintenance will be required. Similarly, condition-based maintenance [40] also relies on the actual condition of equipment; however, the approach that is used to determine the condition of the machines differs significantly.

Condition-based maintenance can be defined as equipment maintenance performed when certain indications imply performance degradation. Predictive maintenance [26] relies on advanced statistical methods and ML to dynamically define when a machine needs to be maintained. It looks at patterns across all sensors and makes one multivariate prediction model. The more the data sources and data available, the better the predictions. For this reason, predictive maintenance models usually get better at predicting future breakdowns over time.

Predictive maintenance can find complex indications for breakdowns which will be nearly impossible for humans to spot. However, the results of predicting future breakdowns span from minutes to month depending on the quality and frequency of data available, as well as the ML methods applied. Both data scientists and domain experts should be involved in the data collection process to ensure that the data gathered is suitable for the model to be built. Then it becomes possible to decide which modeling techniques should be used with the available data and the desired output.

There are multiple modeling techniques for predictive maintenance, and the two most used are regression models to predict remaining useful lifetime (RUL) and classification models to predict failure within a given time window. Both classification and regression use supervised ML methods, which model the relationship between features and the degradation path of the system such as part failure, overheating, etc. In the context of predictive maintenance, we might not predict the failure at the exact moment the machine fails. However, we would rather have some predictions prior to this happening, indicating that something is wrong. It means that we are interested in how well our model correctly predicts the probability of future breakdown. Therefore, traditional supervised learning methods need to be adjusted for prediction purposes. The main change is in the label construction methods—how to choose the labels for the failure cases and the labeling strategies. More details can be found in the section of modeling techniques in [41].

When applying different regression and classification ML models for predictive maintenance, some practical issues need to be addressed as well, such as time-dependent split, handling imbalanced data/sampling methods, cost-sensitive learning, and so on, as listed in [41].

2.4.2 Next Steps

Data imbalance is one of the main challenges when applying ML for predicting failures because failures are relatively rare events, e.g., breakdowns in wind turbines.

Moreover, the time series data is usually imperfect and incomplete due to the malfunctions in the sensors and data recording process [42]. Pure data-driven ML might not be the best choice in this case. More advanced ML methods such as transfer learning [37] and hybrid AI [43] are necessary. In addition, predictions from models and causes must be understood by the domain expert (e.g., the wind turbine technicians), why the model believes something is the cause of the problem, so explainability is also important [44].

Transfer learning [37, 45] is a research problem in ML that focuses on applying knowledge gained while solving one problem (source) to a different but related problem (target). For example, knowledge gained while learning to recognize passenger cars could be applied when trying to recognize trucks. In the context of predictive maintenance for wind turbines, the knowledge gained on synthetic data from high-fidelity wind turbine simulators could be applied to real data collected from the wind turbines.

There are different transfer learning algorithms that transfer knowledge from source to target at different levels: data, features, and model. As reviewed in [46], a very broad categorization would be instance-based approaches (augment the target training data with source data and apply selection and weighting based on similarity/ relevance for the target data/problem), feature-based approaches (map features from source and target data into a shared feature space where the data is more similar to each other, and train models on the combined, mapped data), and model-based approaches (transfer knowledge at the model/parameter level, modifying or co-training models between source and target). Specifically, the pre-train-refine model-based approach is most common when applied to neural networks [47], but it can also be applied to gradient tree boosting for wind production forecasting [48].

When judging the suitability and feasibility of the transfer learning algorithms, it is important to address the following research questions: In which situations can a model be trained on similar or synthetic data and then transferred to actual data? How similar (e.g., size, characteristics, distributions) must the data be for transfer learning? What is the inherent uncertainty induced by the differences between actual and synthetic data? How to quantify the uncertainty and provide safe limits of usage resulting from the transfer?

The time series data from the low-quality sensors and recording systems of the running devices (e.g., wind turbines) is often of poor quality; it is noisy and incomplete and might contain errors regarding the physical attributes of the devices [42]. Real-world data rarely provides a perfect description of a relevant system. Some systems are affected by stochasticity beyond what is represented in the training data. This may prevent ML models from being successfully applied, e.g., due to a lack of trust in the results caused by unsafe extrapolations. Therefore, data-driven ML models need to be constrained by using the underlying physics of the physical models, that is, hybrid AI [43].

There are several ways to implement physical constraints in data-driven models, either in the model structure itself by using special loss and activation functions and features, as postprocessing, or by implementing data-driven models in analytical expressions [43]. There are two types of constraints: soft and hard. Soft constraint is encouraged but not forced to comply, while hard constraint is guaranteed to be satisfied. Examples for soft constraints can be constraints that are integrated into loss terms. Examples for hard constraints can be constraints that are applied as additional non-trainable layers with physics input in the top of neural networks or feature transformation and reduction to fewer units through dimensional analysis which preserves the physical equations as a preprocessing layer.

Some ML models such as Bayesian neural networks (BNNs) in theory can integrate the physical constraints through probabilistic modeling. However, the problem is how to use priors at various stages in BNNs to enforce physical constraints. Moreover, these networks are usually computationally expensive.

2.4.3 End Goal

The two approaches transfer learning and hybrid AI can be combined for solving problems in this use case. However, both are evolving research fields, especially hybrid AI. They require specific solutions given the case at hand, allowing us to use our domain knowledge, but without a clear methodology for operationalizing them. TrønderEnergi is in the early stage of investigating different methods, including using synthetic data generated from simulators and real data collected from sensors of the wind turbines. We are collaborating with academic and industry partners working with this approach under the umbrella of Norwegian Research Center for AI Innovation (NorwAI) [49].

3 Conclusion and Future

This chapter introduced the current and future electric power system with special focus on trends in Norway. Along with the radically changing power system evolution and rapidly developing innovative technologies, it brings a unique set of challenges and opportunities for the energy management systems. Digital transformation is imperative for most of the energy companies, including TrønderEnergi, as their digital solutions stay in different maturity levels for various applied areas of the power system. Use cases for hydropower and wind power trading and predictive maintenance on the upstream have been introduced in detail according to the experience that accumulated in TrønderEnergi. Hydro and wind trading use cases have been successfully applied to the daily working process with added values, while predictive maintenance use cases are still in research and development.

3.1 Positive and Negative Consequence of Digital Transformation

The digital transformation has both advantages and disadvantages. The positives include more competitive businesses, more productive employees, and improved customer experience [50]. These are achieved in our use cases. Automation reduces manual work and potential for human errors in the daily operations. At the same time, it provides more interesting and valuable tasks to the operators. Moreover, digitalization also standardizes the process, so that it relies less on the expertise and experience of individual operators.

Away from the daily routine tasks, the employees are forced to work with more challenging tasks. They need to learn new skills. However, every person has a different tolerance for stress factors, especially those who get used to routine work. Thus, it is important to provide workers with the support they need to feel motivated and feel secure in their jobs.

Every participant in the power market is focused on digitalization to increase efficiency and occupy new niches. More conservative participants are left behind. Digital transformation makes the business more competitive. Well-suited transformations allow businesses to be more flexible, efficient, and productive, which all help to increase the return of investment [50].

Effective implementation of new digital transformation takes time and effort. Moreover, technological progress is, for the near future, unending. That means that digital transformation must be an ongoing process. The digital market is fast and furious in its evolution. When new solutions enter the market, companies have to be ready to apply them quickly.

3.2 The Role of ML in Digital Transformation

Two stages as defined in Sect. 1.3 can be enabled by ML and are related to digital transformation:

4. **Forecasting**: ML can be used to make more accurate point and probabilistic forecasts. Higher accuracy often creates value within the existing business model. Moreover, it also brings the possibility for new services and business models. Even more value is created when forecasting is automated and scaled to new assets and clients.
5. **Autonomy**: Automatic decision-making and autonomous control are difficult to achieve with a sufficient level of robustness and explainability. The outputs of traditional black box ML methods can be hard to explain and guarantee their correctness. Therefore, "explainable" and "trustworthy" ML are often required for industry applications. Currently, humans are responsible for making decisions and providing explanations, using outputs from ML systems to support them.

The use of ML can bring scale, scope, speed, and automation to organizations and enable new services and business models. It does require that humans change the way they work, adapt, and learn new skills and jobs.

However, learning is not only for humans but also for machines to have better forecasts in stage 4 and autonomy in stage 5. Classic ML learns from data through trial-and-error learning, which is costly, slow, and context dependent and often lacking data as input and explanation as output. With limited available data, transfer learning can be used to utilize data from other related sources, or simulations can be used to produce infinite amounts of relevant data for training. For control tasks that optimize long-term cumulative reward, reinforcement learning can be used as an alternative to rule-based and reactive controllers. Reinforcement learning is investigated for model predictive control to achieve energy savings in assets such as buildings and industrial facilities, where models are calibrated from data collected from interactions with the environment.

Sometimes, both human and machine need to learn jointly, which is called meta-human systems [51]. Hybrid human/machine learning systems exhibit major differences in scale, scope, and speed of learning. Meta-human systems come with higher-level cognitive skills that affect the speed of organizational learning and shape the scale and scope economies of organizations in new ways for delegating, monitoring, cultivating, and reflecting [51]. This approach has the potential to accelerate digital transformation.

3.3 Cybersecurity and Regulations

In [52], it is reported that over 7 million data records get compromised each day and incidents of cyber fraud and abuse increased by 20% in the first quarter of 2020. Online criminals, hackers, and even just bored mischief-makers lurk in the shadows, waiting to rob you, commit fraud, and steal your identity.

When all data and processes of a company or industry are digitalized, cybersecurity becomes a paramount concern. The increased reliance on the internet means the company has a lot more to lose if something goes sideways [51]. The loss not only includes data loss but also loss of control of devices and assets. This is especially dangerous for critical infrastructure such as power plants, hospitals, and transportation. Given the increased risks, technical cybersecurity measures (e.g., firewalls, antivirus software, biometrics) are not enough. Regulations from the government should facilitate protection of the digital ecosystem.

3.4 Digital Ecosystem

A digital ecosystem is focusing on bringing extra value to customers by optimizing data and workflows from different internal departments, tools, systems, as well as customers, suppliers, and external partners, as defined in [52]. It should remove obstacles from the customer journey and enable every participant in the ecosystem to use state-of-the-art technologies and systems to fulfill their individual needs.

These ecosystems offer customers a unified and easy-to-use system that delivers value through a variety of services, products, and insights. This also allows the platforms to grow exponentially and outpace the normal market by using several mechanics involved [53].

The use cases we have described are just parts of the whole digital ecosystem for the electric power system. More integrations are foreseen, for example, hybrid pumped hydro and battery storage for intermittent wind power [54], smart grid [9], and a range of services to consumers. The five key characteristics of a digital ecosystem are customer-centric, data-driven, automated, global, and dynamic [53]. Starting from the digital transformation on the upstream, there is a long way to go for digital electric power ecosystem to reach its full potential.

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