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Autonomy: Enabler of the Sustainable and Intelligent Power System

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Abstract

Power sector has been under permanent change for years in the dawn of two highly intertwined revolutions: the autonomy revolution and the revolution of power systems. On one hand, the power grids worldwide face growing challenges related to efficiency, for example changing supply and demand patterns ambiguity and on the other, new digital technologies are paving the way to a new way of managing systems. In this work, we are addressing where, why and how: where the autonomy could be implemented in the power grids, why it should be implemented and through an example related to the system stability, a pioneering approach on how it could be implemented. This work is the part of Kopernikus Project ENSURE effort, which is giving insights into the power grid of the future and the innovative means to control it.

1 Introduction

Browsing any news portal (or just by looking at the headlines of the newspaper), talking to virtually anyone we know in the last months, it seems that the topic of Covid-19 is simply unavoidable. While the immenseness of the crisis that the pandemic provokes is something we are trying to completely grasp and understand, in this manuscript we are not planning to focus on the negative impacts that the pandemic caused. On the contrary, in this manuscript we focus on the potentially game-changing implications that a situation as disruptive as this leaves on the way we, engineers, work and how we operate the electrical grids.

The coronavirus is accelerating the digital transformation of society and the economy, and we should seize the resulting opportunity. Digitalization of work [1] is progressing: companies are relying heavily on digital technology to remain in contact with their customers – not only through video calls, but also by using digital platforms to deliver remote services that keep businesses running. We might say that this disruption is enabling technologies to grow and take their place in the world, changing the habits we operate but not necessarily with the negative impact.

Digitalization is penetrating also the power sector and the disruption such as Covid-19 is speeding up this process [2]. However, the power industry is not starting from scratch, to start with. Our sector has been under permanent stress for years in the dawn of two highly intertwined revolutions: the autonomy revolution and the revolution of power systems. One is actually unthinkable without the other.

The power sector worldwide faces growing challenges related to quality, for example changing supply and demand patterns ambiguity [3]. Integrating intermittent renewable energy is making power systems increasingly intricate. The number of active components is dramatically growing, the system is increasingly dynamic and characterized by a stochastic behavior. In particular, the almost arbitrarily scalable technology of photovoltaics lead to a profound structural change of the power systems. While in the past, a relatively small number of large power plants had to be coordinated in order to cover a predictable and relatively slowly changing load, the future power systems' generation potential will be yielded by a plurality of small units and substantially more dynamic processes of their coordination and dispatch to be handled transparently in real time. The growth of number of prosumers causes bidirectional flows of energy which are difficult to predict, further complicating both the operation of distribution grids and the planning and coordination of protection systems. Finally, the growth of electric loads including electric vehicles paves the way to an increasing energy demand, not only in its volumes but also the unpredictability. In this new reality, maintaining high standards of safety, reliability and quality of energy supply is becoming progressively challenging [3].

Nevertheless, the digital links that connect the individual system components such as generation, dynamic loads and grids between them provide valuable data. Plurality of sensors and meters connected with appropriate communication technology serve as the fundament for collection and processing of the huge amount of data in the grids. If on top of this architecture, an intelligent system can analyze these streams of information, the resulting impact can improve system management and control and detect potential alarming events earlier to prevent faults before they arise. By intelligent system we assume (semi-)autonomous software agent which can adapt to variable and non-anticipated conditions due to its capability of learning through interaction with the environment [4].

Equipped with the capability of such an interaction and learning from available data and actions made by operators and control automation, the agent is capable to self-adapt and learn. As elaborated in [3], the autonomy is not a single piece of technology, but rather a plurality of technological software and hardware enablers, such as artificial intelligence (AI)/ machine learning (ML), digital twin, sensors, advanced ICT, distributed computing etc.

Consequently, the implementation of the agent can be based on synergies of those enabling technologies. In this

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work, we describe such an autonomous agent on the example of transient stability problem based on ML. It is capable to learn the possible contingencies in the offline mode and then act almost instantly when the contingence occurs. In that way it can overperform the traditional automation which is not capable to explicitly calculate dynamic behavior in real time due to complexity of underlying necessary simulations.

2 Adoption of the autonomy in the power sector

The electrical utilities are increasingly embracing the concepts of autonomy and implementing digitalization technologies. In the questionnaire by SAS [5], management, executive and professional staff of the energy (mainly electrical) utilities in USA and worldwide have been asked to provide their view on importance of innovative technologies and the employment of autonomy. One of the findings was that in just two years, a sound increase of the interest and the implementation of the autonomy concepts have been achieved (**Figure 1**). Percentage corresponds to the number of positive answers on the above questions.

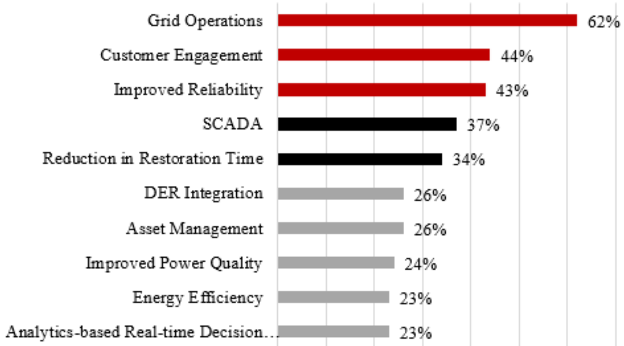

Figure 1 Importance of the autonomy implementation per topic as viewed by electrical industry decision makers [4]

Another interesting finding was to which domains in utility business do the respondents recognize the primary or planned use of digitalization technologies (**Figure 2**). The higher the percentage, the more respondents selected the appropriate use in their top 5 uses. The study demonstrated clearly the penetration of these new technologies in power sector.

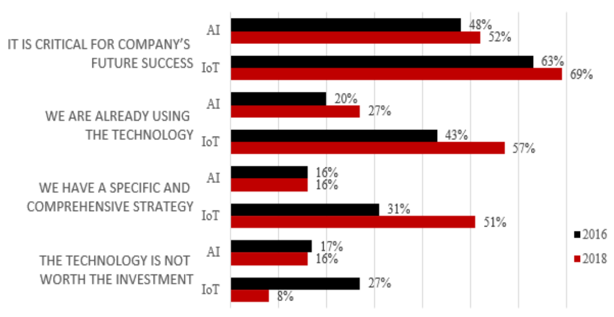

Figure 2 Primary or planned use of digitalization technologies [4]

2.1 Sector applications

Implementation of autonomy is enhancing quality of managing the systems and transparency while making infrastructure more robust and reliable – for example, by using smart grids to link prosumer systems with the rest of the power grids. Once merely isolated passive demand, today's prosumers are prime areas of application for advanced monitoring and distributed control of the energy systems. These connected facilities are becoming active contributors within the power grid by supplying energy and data.

Provision of the appropriate communication technology and bandwidth between various sensors on prosumer premises can unlock huge potential. For example, buildings account for around 40% of global energy consumption, but an average building still wastes up to 50% of the energy it consumes [6]. Here, a lot of money could be saved while simultaneously protecting the environment and this is just one of the segments of an entire electrical energy ecosystem that could be optimized. In our paper we would like to highlight the potential of autonomy in the quest for sustainable energy future.

The implementation of digitalization technologies across the power system lifecycle could reduce the costs in at least four ways: by reducing operations and maintenance costs; improving power plant and network efficiency; reducing unplanned outages and downtime; and extending the operational lifetime of assets. In its report on digitalization in energy [7], IEA argues that the overall savings from autonomy enabled measures in the next decades could be quite substantial. These savings originate in the enhanced global deployment of available digital technologies to all power plants and network infrastructure.

Implementation of the autonomy can reduce O&M costs, enabling predictive maintenance, which can lower costs for the owner of plants and networks and ultimately the price of electricity for end users [4]. Over the period to 2040, notable reduction in O&M costs achieved through digitalization could save both the companies and the consumers considerable resources.

Autonomy could help achieve greater efficiency through improved planning, enhanced efficiency of combustion in power plants and lower loss rates in the power grids, as well as better project design throughout the overall power system. These topics have been already tapped in the industrial and academical domains and the first real-world implementations are in place. Some of the leading suppliers have recently rolled out the digitalized ecosystems, e.g. for transformers [8]. On the market, we see the emerging of the portfolio of solutions, like the "digital enterprise", that encompass energy portfolio management, network control systems and management of assets performance and workforce [9].

Innovative systems like those can yield efficiency gains by lowering the rate of losses in the delivery of power to consumers which impacts the sustainability, for example through remote monitoring that allows equipment to be operated more efficiently and closer to its optimal conditions, and flows and bottlenecks to be better managed by grid op-

erators. The greatest transformational potential for autonomy concepts deployment is its ability to break down boundaries between energy sectors, increasing flexibility and enabling integration across entire systems.
In this manuscript, we analyze the potential benefits that autonomy can have for the users and the power utilities, focusing on the analysis of the power system resilience and the way autonomy could bring the leverage. The autonomy can reduce the frequency of unplanned outages through better monitoring and predictive maintenance, as well as limit the duration of downtime by rapidly identifying the point of failure. This increases the resilience and reliability of supply and can have positive effects on the costs. Network failures are expensive, both for the utility and for the economy.

3 Power system resilience

In the electrical grids, resilience is defined as the ability of system to limit the extent, severity, and duration of system degradation following an extreme event. Power system resilience is closely intertwined with and functionally inseparable from reliability. Reliability is aimed at reducing the probability of power interruptions, while resilience is aimed at reducing the damage from outages and shortening outage durations.
This makes it a primary consideration for electricity transmission and distribution operators [10]. To strengthen the system reliability, the requirement is to continuously supply adequate generation to meet demand and react dynamically to both random and routine changes within the system. Incapability to maintain the system in balance can lead to a blackout in a worst case.
In a distribution grid, resiliency means the ability to avoid severe damages to the distribution infrastructure caused by extreme events and to restore as much as load as possible in a short time after major outages. Moreover, frontier risks in the form of cyber-attacks are becoming a reality, and will require new data driven approaches to tackle, given the nature of blackouts in the past were mostly hardware related, often caused by equipment faults from fallen trees, animals or vehicle accidents [11].
Finally, apart from external risks, the energy transition is the driving force of the revolution of the power grid. Brought largely by the need for decarbonization, and increased geographical interconnection, power grids are becoming more complex and increasingly unpredictable [3]. Some factors contributing to this increased complexity are more renewable energy sources (RES) being embedded in local distribution systems, electric vehicles, heat pumps, high voltage DC interconnectors and smart grids with their associated control systems. These factors are affecting in both positive and negative way the distribution grids.
We can classify approaches aimed at forging the resilience of distribution grids in the following categories [12]:

- Construction programs: reinforcement of the utility poles and overhead distribution lines. This also includes, when possible, an exchange of the overhead lines with the underground cables
- Maintenance measures: exchanging the assets nearing end of lifetime, vegetation management as well as running the vulnerability analysis
- Advanced autonomy/automation technologies: smart infrastructure is essential for the resilience of the distribution grids. This infrastructure is composed of advanced metering infrastructure (AMI), modern communication and control, Distribution management and outage systems (DMS/ OMS), already mentioned DERs but also controllable loads, electrical vehicles and microgrids.

Apart from internal factors which test the resilience of distribution grids, it is fair to note that many outage events were provoked by the problem propagation from the external higher voltage grids, namely due to cascading events in the connected transmission grid. There is a necessity to tackle these potentially catastrophic events and the autonomy technologies could play the vital role.

3.1 Blackouts and system resilience

System outages are extremely expensive. Even short-term outages can result in significant economic damage, both to energy suppliers in the form of maintenance and lost revenue, but also to end users through loss of earning or contingency expenses.
There is a strong correlation between the number of outages and frequency of irregular weather conditions). Weather events are the leading cause of blackouts worldwide, but this factor is followed closely by human error or equipment failure events (**Figure 3**).

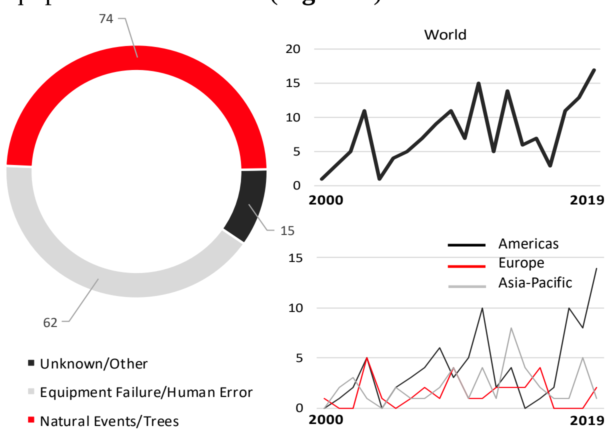

Figure 3 Causes of major blackouts worldwide and their incidence [13]

These trends are foreseen to increase due to climate change; consequently, the number of outages will grow as the result of an increased rate of urbanization and inflating electricity demand in the developing world.

3.2 Power grid stability

Power grid stability can be defined as the system's ability, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact [14], and is

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governed by three elements; rotor angle, frequency and voltage stability.

Blackouts do not occur instantaneously following a disturbance (often referred to as a contingency). Rather, they occur as the result of a sequence of events, known as cascades [15]. These complex events can occur over a period of several seconds to minutes, following an initial contingency. They are usually the result of grid protection systems tripping a piece of equipment to protect it from damaging conditions.

The most common scenario is under frequency, where demand exceeds supply. This could be the result of multiple trappings in the network, disconnecting generation from load centers [16].

While system frequency is a primary feature of interest with respect to large scale blackouts, it is often a secondary consequence of rotor angle instability (or transient instability) [17], which can typically occur within a matter of hundredths of a second from a fault clearance. What makes these events particularly difficult to anticipate is the speed by which transient instability can occur. Transient stability is concerned with the ability of all synchronous machines in the system to remain in synchronism following a disturbance. In the case one machine runs faster than another, the angular position of the rotor of the faster machine will advance on the slower one and transfer some load from the slower machine.

In event of such a disturbance, the system will remain transient stable if the oscillations diminish and all machine angles return to a new steady state. In a transient unstable case, angular swings of one or more machines will increase until they are tripped to avoid pole slipping (generally a machine's relative rotor angle is not allowed to exceed 180 degrees). It is highly challenging to anticipate rotor angle behavior following a contingency since it is dependent on the initial operating conditions of the system (which change in real time), and the severity of the disturbance (which cannot be anticipated). However, having some indication of how rotor angle trajectories would evolve following a contingency could be greatly beneficial in preventing subsequent cascades. Following chapter explains the implementation of the autonomous agent [4] based on ML following the discussion from the introduction of the paper. The solution to this and similar stability related problem using ML has been gaining momentum lately and has been tackled in several works, such as [18], [19], [20].

4 Machine learning in transient stability analysis

Any contingency can be simulated offline using dynamic power system software packages. These simulations are, however, computationally expensive, typically involving thousands of differential equations solved through numerical integration. Given the short time scales of interest with respect to transient instability, it is not feasible to explicitly calculate dynamic behavior in real time. **Figure 4** highlights these time constraints by presenting the time from a single line failure, and a generator being disconnected from the system due to transient instability for a sample of contingencies simulated using the IEEE 118 bus model.

The majority of pole slipping events take place following the primary rotor angle swings on a time scale of approximately 0.5 seconds following fault clearing, extending to 2 seconds for secondary and tertiary swings. In reality, an autonomous control system may have a fraction of a second to forecast an issue spatially and temporally, define a most suitable mitigation strategy, and implement this strategy through the emergency control and protection schemes.

The IEEE 118-bus model was chosen as a case study in this work to evaluate the performance of machine learning models on a larger system, with greater inertia, therefore producing benchmarks which may be a closer reflection of real-world systems.

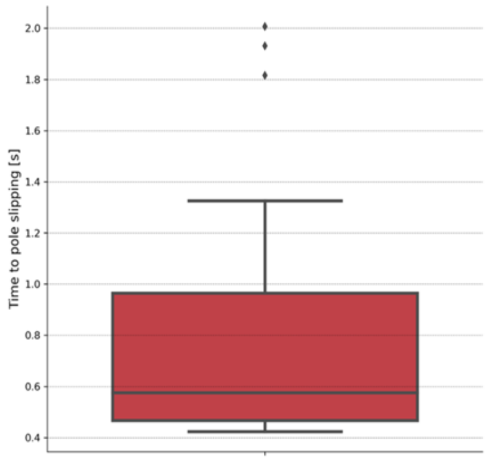

Figure 4 Average time in seconds to a generator pole slipping for a sample of 30 transient unstable events simulated for the IEEE 118 bus system

As the study requires dynamic model, each generator is connected to the high-voltage transmission system through ideal transformers. As a result, the 118-bus model used in this study contains 172 buses, 185 lines, 76 transformers, and 91 loads which consume a nominal load of 3668MW and 1438 MVAr.

4.1 Data generation and processing

Given the increasing contribution of wind and other static forms of generations in power grid (i.e. solar), various configurations of the grid dynamic model were made, and the effects of increased wind penetration, and hence reduced spinning reserve were analyzed.

The dataset generated for this study consists of 1200 simulations. Each simulation is distinct and sampled at 0.001 second time steps. Each simulation starts at -20 seconds to allow the system time to adjust to steady state. A fault then occurs at time 0 - (clearing time), and time series data is recorded from 0 - 5 seconds. Each simulation therefore consists of 5000 timesteps.

In the data preparation part, by running a Fast Fourier Transform on the time series, it was found that the most important frequencies lied between 0.5 and 0.7 seconds.

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The data was then split into training, validation and testing sets. The split was made yielding 70% of the data for training, 20% for validation and 10% for testing.

4.2 ML models and architecture

In this study, the neural networks were used to find an optimal function $y = f^*(x)$, which maps an input sequence vector x to an output vector sequence y. A neural network defines this mapping as $y = f(x; \boldsymbol{W})$ where the networks parameters $\boldsymbol{W}$ are learnt in a stage wise fashion to produce a best function approximation. A number of non-sequential models were evaluated to determine whether significant performance gains could be achieved from more complex neural networks, among them baseline linear, LSTM and autoencoders. LSTM conducts back propagation through time and can store long term sequential dependencies. LSTM network is a series of neural networks which feeds information between cells using a for loop [21].

An autoencoder is a pair of functions, $h: \mathbb{R}^d \to \mathbb{R}^m$ and $g: \mathbb{R}^m \to \mathbb{R}^d$, where d is the dimensionality of the original space and m is the dimensionality of the autoencoder embedding (or compression) [22]. In this work, h is a two-layer bidirectional LSTM network, with 200 units and 60 units respectively, g contains a repeat vector, which copies the embedded space in a row wise fashion by the length of the

input sequence and is followed by a bidirectional LSTM layer with 200 units and a fully connected dense layer which learns to reconstruct the sequence (**Figure 5**). The reconstruction error for $f(h, g)$ is optimized by mean absolute error (MAE). Without the autoencoder block, models need to be trained on fixed input-output sequence lengths.

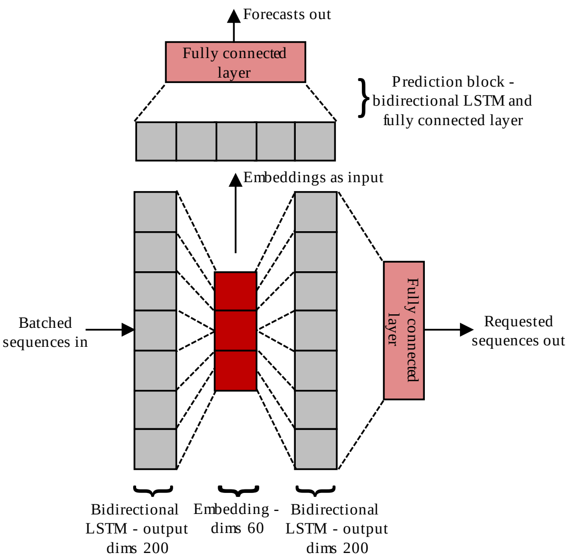


Figure 5 Encoder-decoder architecture

It is therefore possible that the autoencoder block could be retrained frequently in a real-world scenario independent of the forecasting block, increasing the quality of embeddings due to an increased exposure to real-world PMU data.

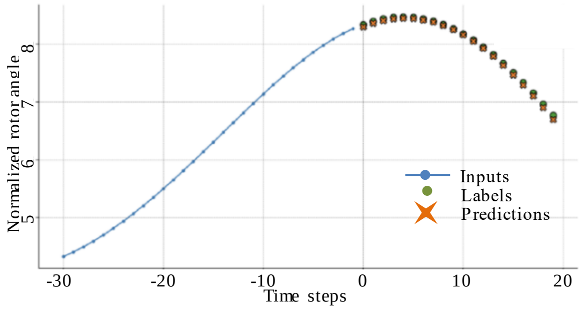
4.3 Results and conclusions

Throughout the training process, model performance was monitored using the validation dataset, the test set was held out during training, and only used to show performance on unseen data. Multiple loss functions were explored, and their performance examined on the validation set. It was found that MAE ($\sum_{i=1}^{N} \|y - \hat{y}\|$) yielded the best performance.

Figure 6 shows the predictions for the best performing model i.e. encoder-decoder for a selected prediction window. Inputs refer to the actual rotor angles with respect to the input features.

We can conclude that, at the cost of increased model complexity, PMU signals can be effectively used as input features to machine learning models to forecast relative rotor angles and can even result in increased performance.

Figure 6 Encoder-decoder model predictions



Analyzing the full-time horizon, **Figure 7** shows a complete set of time series prediction for two machines in the system. It can be seen that the predictive accuracy is higher in the last two thirds of the time series, with peaks in model uncertainty during the early transient swings in the series. This is likely due to dataset imbalance. The system is naturally damped, so the model has trained on a greater number of sequences with small swing amplitudes that critical larger swings.

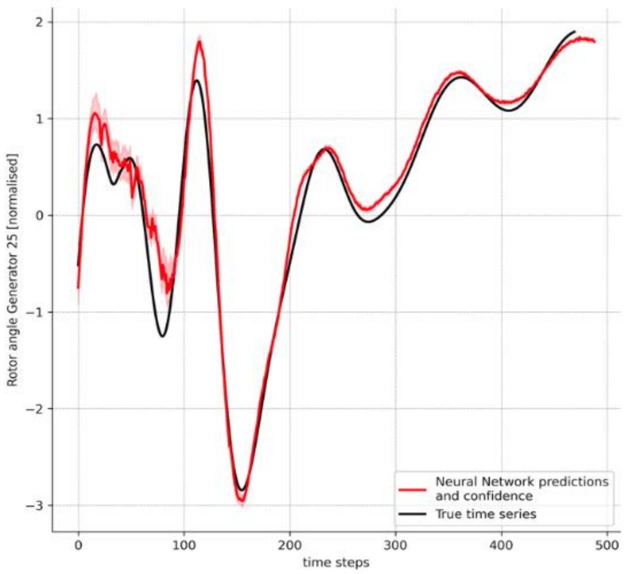


Figure 7 Example of an LSTM sequence prediction for a single contingency and single generator

Extending the length of time series to train machine learning models would exacerbate this issue, however, it is important to forecast beyond the primary swings of the system to capture dangerous islanding effects, where the system is not technically unstable. Supplementing model training with shorter time series could help address the issue.
While the results are promising, a number of limitations were identified which limit such a model's suitability in a real-world setting. These limitations will be explored in further work. The first limitation is that the model showed diminishing performance when the network topology was changed from the fixed topology it was trained on. In an interconnected grid, topology changes are increasingly routine, and may currently cause prediction errors. The IEEE model used to generate training data represents ideal case where PMU signals are available at each network bus. This ideal case is not reflected in many grid networks globally, and further work needs to be conducted to determine the performance of such a model where data inputs are spatially sparse. Further, unlike traditional 'rule based' algorithms, it is difficult to guarantee the performance of the model on all possible failure cases in the real work, since there are an infinite set of possible system operating conditions. Therefore, the Bayesian approximation was used to provide a metric of model uncertainty. With such a metric, a minimum threshold of uncertainty could be defined, and model predictions discounted of outside of this range.

5 Risks and chances of the implementation of the autonomy in the power utility business

As stated in the previous chapters, autonomy provides multiple chances to support and improve operators in the power utility business. However, as any other new idea or concept, the path towards autonomy bears certain risks. Some general thoughts on potential risks and open discussion points are stated below, combined with the question: what is the most beneficial level of autonomy for the power utility sector?
A first potential risk could be the loss of know-how and strong dependence on the "black-box" system. In many occasions we rely on human's expert-knowledge or innovative thoughts on how to handle certain situations or develop new ideas on useful implementation – especially in previously unknown situations. One example would be the autopilot mode in airplanes: pilots rely on such systems but in critical situations, they take over the control.
Another threat can be seen in a growing risk of cyber security due to the rising number of autonomy players and digital interfaces (e.g. smart meters).
Further review points include the responsibility in case of e.g. a system failure or personal injuries. Should the software developer or the applier be hold responsible? And what should be target function of an autonomous system? Should it only target the minimization of costs or also target climate goals or social aspects? And if one considers the costs: many components – which provide the basics for autonomy, such as a growing number of sensors and communication technology- come with a price. In some cases, these costs exceed the costs of the conventional alternatives. Therefore, when continuing our path to a (semi-)autonomous system, we should always include in our decisions a cost-benefit-analysis.
Overall, it can be stated: autonomy will provide great chances for the power utility business, but it has to be applied in a conscious and goal-oriented way.

6 Conclusion

Building up on the revolutions in power systems and the digitalization, it is necessary to explore innovative and unorthodox but promising technological advancements. In this paper, it was explained how and where the autonomy could become the integral part of power systems through the realization of a (semi-)autonomous intelligent agent. To motivate the use of such an agent, the field of power grid reliability and stability was chosen. The problems that occur in the modern power systems related to stability and an insight how a machine learning based autonomous agent could help in resolving the issues were exposed. Chances and the risks from the operator's perspective were also documented. It was concluded that such technologies could play important, if not crucial role in the power systems.

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8 Literature

[1] C. Warhurst and W. Hunt, "The Digitalisation of Future Work and Employment. Possible impact and policy responses," 2019. [Online].

[2] C. Vergueiro Massei, "COVID-19 will accelerate the revolution in energy systems", World Economic Forum, 2021. [Online]

[3] V. Biagini, M. Subasic, A. Oudalov and J. Kreusel, "The Autonomous Grid: automation, intelligence and the future of power systems," *Energy Research & Social Science,* vol. 65, no. 1, 2020.

[4] M. Subasic, V. Biagini, A. Oudalov, J. Kreusel, I. Hebbeln, M. Rose and T. Pletzer, "On the Path to Autonomous Power Management," in *CIGRE2020*

[5] SAS, "The Autonomous Grid in the Age of the Artificial Intelligence of Things," 2018. [Online].

[6] The World Business Council for Sustainable Development, "Energy efficiency in buildings,", 2009. [Online]

[7] IEA, "Digitalization and Energy," November 2017. [Online].

[8] Hitachi ABB Power Grids, "TXpert™ Ecosystem," September 2020. [Online].

ETG-Kongress 2021 . ISBN 978-3-8007-5549-3 . ©VDE VERLAG GMBH . Berlin . Offenbach

[9] Hitachi ABB Power Grids, “Digital Enterprise,” 2020. [Online].

[10] C. Singh, P. Jirutitijaroen and J. Mitra, “Introduction to Power System Reliability,” in *Electric Power Grid Reliability Evaluation: Models and Methods*, Wiley-IEEE Press, 2019, pp. 185-191.

[11] S. Sheng, W. Yingkun, L. Yuyi, L. Yong and Y. J., “Cyber attack impact on power system blackout,” in *IET Conference on Reliability of Transmission and Distribution Networks*, London, 2011.

[12] Y. Xu, C. Liu, K. Schneider and D. Ton, “Toward a Resilient Distribution System,” in *IEEE Power & Energy Society General Meeting*, Denver, 2015.

[13] ABB Power Grids, “Blackouts and power system resilience,” Hitachi ABB Power Grids, Zurich, 2019.

[14] P. Kundur et al., “Definition and classification of of power system stability ieee/cigre joint task force on stability terms and definitions,” *IEEE Transactions on Power Systems,* vol. 19, no. 3, pp. 1387-1401, 2004.

[15] K. Yamashita; J. Li; P. Zhang; C. Liu, „Analysis and control of major blackout events,“ IEEE Power Systems Conference and Exposition (PES), Sattle, 2009

[16] V. Muzik, V. Vajnar, “Frequency and voltage stability assessment of a power system during emergency service states,” IEEE EIConRus, Moscow and St. Petersburg, 2018

[17] J. Yie, C. Liu, U. Vaidya, “A PMU-based monitoring scheme for rotor angle stability,” IEEE Power and Energy Society General Meeting, San Diego, 2012

[18] S. K. Azman, et al., „A Unified Online Deep Learning Prediction Model for Small Signal and Transient Stability,“ IEEE Transactions on Power Systems, vol. 35, no. 6, pp. 4585-4598, 2020

[19] Y. Chen, et al., “Rotor Angle Stability Prediction of Power Systems With High Wind Power Penetration Using a Stability Index Vector”, IEEE Transactions on Power Systems, vol. 35, no. 6, pp. 4632-4643, 2020

[20] J. Hou, et al., “Power System Transient Stability Assessment Based on Voltage Phasor and Convolution Neural Network,” IEEE International Conference on Energy Internet (ICEI), Beijing, 2018

[21] I. Goodfellow, Y. Bengio and A. Courville, “Deep Learning”, MIT Press, 2016. [Online].

[22] T. Su, et al., “Probabilistic Stacked Denoising Autoencoder for Power System Transient Stability Prediction with Wind Farms,” IEEE Transactions on Power Systems (early access), 2020