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FLEXIBILITY IN POWER SYSTEMS

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Summary

Modern power systems rely on power generation from renewable sources, predominantly from wind and solar. However, the intermittency and variability of these sources require additional power system flexibility. Due to retirement of conventional thermal generation, the need for flexibility is increased, while the flexible resources are reduced. Thus, new flexibility resources are sought. This paper examines real-world examples of the increased flexibility requirements, identifies the new sources of flexibility in the form of batteries and demand response, presents relevant mathematical models, and provides guidelines on future research needs in this area.

Keywords: exibility; renewable energy; battery storage; thermostatically controlled loads

1. CONTEXT AND MOTIVATION

A combined system for generation, transmission and distribution of electricity is argued to be the most elaborate and most life-changing system that human kind has ever developed. Despite its complexity, the entire power system operation can be boiled down to one simple rule – electricity generation and consumption must be balanced at all times. This balance is reflected in the measured value of frequency in a power system. While North American and some countries in Asia chose the nominal frequency to be 60 Hz, the majority of countries adopted 50 Hz nominal frequency. Regardless of the nominal frequency level, the actual frequency levels should not significantly depart from this value. The main reasons for frequency deviations can be attributed to either i) poor prediction of load and variable renewable generation, e.g. wind solar power plants, or ii) failure of a generating unit or a network element, e.g. circuit breaker, transmission line, transformer. While the load prediction error is commonly within 1% of the current load [2], prediction errors related to the output of variable generating units is significantly higher, occasionally surpassing 15% [3]. Thus, the power systems with a high share of variable renewable resources might experience increased frequency deviations due to forecast errors. The other main reason for frequency deviations are power equipment failures. Failure of a generating unit directly affects the frequency, as it disturbs the power balance. Failure of a power line, on the other hand, causes changes in the power flows and may load the surrounding lines above their thermal limits. This can cause tripping of additional lines and even eventually break the power system in multiple islands or even cause partial blackouts. On 8 January 2021, at 14:05 CET, the synchronous area of Continental Europe was separated into two parts due to outages of several transmission network elements in a very short time. The initial event was the tripping of a heavily loaded 400 kV busbar coupler in the Ernestinovo sub- station in Croatia by the overcurrent protection at 14:04:25.9 [4]. The altered power flows caused tripping of many network elements, as shown in Figure 1, and dismantled the European power system into two parts, the north-western one, with insufficient generation, and the southeastern one, with excess generation. Consequently, the north-western part experienced a frequency drop to 49.74 Hz, while the frequency in the south-eastern part increased to 50.60 Hz. To balance these two independent systems, a portion of the interruptible load was disconnected in the north-western part, while the generators in the south-eastern part reduced their power output. After the frequencies in both islanded systems were brought close to 50 Hz again, they were re-synchronized at 15:08 CET and continued the normal operation of the Continental European power system.

Figure 1. Separation of Continental Europe Synchronous Area on 8 January 2021 [4].
Slika 1. Razdvajanje sinkrone zone kontinentalne Europe 8. siječnja 2021.

Normal operational practice within the European power systems prescribes frequency deviations lower than 1% of the nominal value [1]. Such low frequency deviations can be achieved more easily in larger power systems. A generator failure in a system with thousands of generators is easy to deal with, as the remaining generators have sufficient regulation capacity to increase their output and jointly displace the generation of the generator under failure. Thus, large power systems are very robust to unexpected events, which was the main reason for continental Europe to be connected in a single large power system.

To address the issue of balancing the generation and the demand in power systems with a high level of variable renewable generation, and, consequently, with reduced regulation abilities from the reduced number of online controllable generators, the term *flexibility* has become important in both the scientific and technical literature recently. In one of its reports, Electric Power Research Institute defines flexibility as *the ability to adapt to dynamic and changing conditions, for example, balancing supply and demand by the hour or minute, or deploying new generation and transmission resources over a period of years [5].* Power system flexibility is becoming so important that the California Independent System Operator – CAISO introduced new market products, flexible ramp up and flexible ramp down in 2016.

Both the technical needs for flexibility and the researchers' interest worldwide in this topic are the motivation behind this paper, which aims at the following:

- Explaining the increased needs for flexibility in power systems with a high level of variable and poorly controllable renewable energy sources, i.e. wind and solar power plants (in Section 2);
- Identifying and discussing new sources of flexibility in power systems (in Section 3);
- Presenting mathematical models of new flexibility sources (in Section 4).

2. INCREASED NEEDS FOR FLEXIBILITY

Due to the load prediction errors, as well as possible failures of power system elements, power systems have been designed to operate in a way that foresees real-time adjustments in generators' power output levels. In vertically integrated power systems, as well as similarly designed US-type electricity markets, system operation is scheduled one day ahead of the operation. This process is called unit commitment, implicating that decisions are made on the commitment (on/off status) of generating units. This is highly important as thermal generators, especially nuclear and coal-fired power plants, require hours, if not days, to start up. The unit commitment problem aims at minimizing the overall operating costs of the system:

$$\text{Minimize} \sum_t \sum_i c_{i,t} \tag{1}$$

where $c_{i,t}$ denotes operating costs per generator i and time period t. The problem is primarily subject to the following technical constraints:

$$c_{i,t} = A_i \cdot x_{i,t} + \sum_k B_{k,i} \cdot p_{k,i,t} + s_{i,t} \cdot y_{i,t} \tag{2}$$

$$y_{i,t} - z_{i,t} = x_{i,t} - x_{i,t-1} \tag{3}$$

$$y_{i,t} + z_{i,t} \leq 1 \tag{4}$$

$$p_{i,t} = \sum_k B_k \cdot p_{k,i,t} \tag{5}$$

$$P^{\min} \cdot x_{i,t} \leq p_{i,t} \leq P^{\max} \cdot x_{i,t} \tag{6}$$

$$p_{i,t} - p_{i,t-1} \leq R^{\mathrm{up}} \tag{7}$$

$$-p_{i,t} + p_{i,t-1} \leq R^{\mathrm{dn}} \tag{8}$$

$$\sum_i p_{i,t} = \sum_l D_{l,t} \tag{9}$$

Constraint (2) calculates the hourly operating costs per generator, which consist of the fixed operating cost $A_i \cdot x_{i,t}$, the variable operating cost $\Sigma_k B_{k,i} \cdot p_{k,i,t}$ and the startup cost $s_{i,t} \cdot y_{i,t}$. The fixed operating cost is present whenever a generator is on. This is indicated by binary variable $x_{i,t}$, which takes value 1 when generator i is on in time period t, and 0 otherwise. The variable generation cost is based on a piecewise cost curve, where $B_{k,i}$ is the slope of the cost-curve segment k, and $p_{k,i,t}$ power produced within this segment. Finally, the startup cost is present if generator i is started during time period t, which is indicated by assigning value 1 to binary variable $y_{i,t}$. Interaction between on/

off binary variable $x_{i,t}$, startup binary variable $y_{i,t}$, and shutdown binary variable $z_{i,t}$ is modeled in constraints (3) and (4). Constraint (5) sums the generators' production per segment to obtain their overall individual outputs. Constraint (6) is used to limit the minimum and maximum production of each generator. If a generator is off, binary variable $x_{i,t}$ will have value zero and force $p_{i,t}$ to zero. Constraints (7) and (8) are ramp up and ramp down constraints. They limit the maximum change in the generator's power output in between two consecutive time periods, i.e. hours. Finally, the generation–demand balance is imposed in constraint (9). Unit commitment models also incorporate additional constraints on the generator's minimum up and down times, as well as stepwise generator startup costs and power flows [6]. In this paper, they have been omitted for brevity.

Considering the basic unit commitment model (1) – (8) in the context of the power system economics, the most relevant parameters are the ones related to the generator's costs: A_i, $B_{k,i}$ and $s_{i,t}$. However, in the context of power system flexibility, the important parameters are the minimum stable output $P^{\min}$ and the ramp limits R^{up} and R^{dn}. High values of the stable minimum output have detrimental impact on power system flexibility, as it can seriously limit the power output range of a generator. This is especially relevant for systems with a high share of photovoltaics that tend to largely reduce the net consumption curve (net load is equal to the actual load minus the generation from non-controllable renewables such as solar and wind) in the middle of the day. This phenomenon is often referred to as the duck curve (shown in Figure 2).

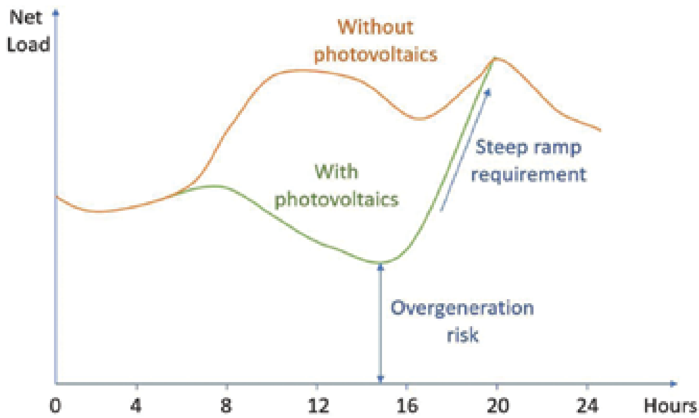

Figure 2. Visualization of a duck curve caused by high penetration of photovoltaics.
Slika 2. Prikaz tzv. krivulje patke uzrokovane visokom penetracijom fotonaponskih modula.

In systems where the online generators have high minimum output limits, the generators need to be turned off in the middle of the day, as they would otherwise cause an over-generation. However, insufficient amount of online generators in the middle of the day may not be able to meet the required steep growth of the net load caused by a simultaneous increase in the actual load and reduced generation from photovoltaics toward the end of the day. For this reason, it is required that online generators have very high ramp limits, characteristic for hydro power plants and gas-fired power plants. However, the downside of gas-fired power plants are high minimum output levels, often reaching 40% of the maximum power output. More details on the duck-curve problem is available in [7].

In order to address the duck-curve issue and sustainably increase the flexibility of the entire system, flexible energy sources need to be appropriately awarded through transparent market mechanisms. For instance, the California Independent System Operator (CAISO) introduced a flexible ramping product in 15- and 5-minute markets, which allows it to procure sufficient ramping capability via economic bids [8].

As opposed to the US-style nodal markets, the European energy markets are zonal. This means that instead of an ISO conducting the network-constrained market clearing as in the nodal markets, in Europe, a Power Exchange conducts a market clearing process without considering the network constraints. This market-clearing process can be formulated as:

$$\text{Maximize} \sum_{t} \left(\sum_{b} q_{b,t} \cdot \lambda_{b,t} - \sum_{s} q_{s,t} \cdot \lambda_{s,t} \right) \tag{10}$$

which maximizes the social welfare, defined as the sum of the producers' profit and the buyers' surplus. Variables $q_{b,t}$ and $q_{s,t}$ denote the cleared quantities of buyer b and seller s, respectively, while $\lambda_{b,t}$ and $\lambda_{s,t}$ denote the buyers' and sellers' prices offered in the market. The objective function (10) is subject to the following constraints:

$$q_{b,t} \leq Q_{b,t} \tag{11}$$

$$q_{s,t} \leq Q_{s,t} \tag{12}$$

where $Q_{b,t}$ and $Q_{s,t}$ are offered the buyers' and the sellers' quantities, respectively. The European-style markets do not include network constraints, so that after the market-clearing process, the market clearing outcome is sent to the system operator to conduct the power flow analysis and, if necessary, perform a re-dispatch of the generating units to keep the network away from an undesirable state.

Obviously, the US-style market clearing process is much more rigorous than the European-style, which is decentralized, and generators, usually combined in balancing groups, need to perform self-dispatching. In transparent European markets, the most of the energy is traded in the day-ahead market, which is cleared a day before the actual delivery of electricity. There are two markets closer to real time: the first one is the intraday market, cleared up to 30 or 5 minutes before the delivery, and the second one is the balancing market, where the system operator activates reserves to cover for the generation–demand imbalance in real time. More information on the European electricity markets is available in [9].

Since the traditional generators, i.e. coal-fired, nuclear and generally all thermal generators besides the fast-starting gas-fired plants, are not responsive enough for trading of large energy volumes in intraday and balancing markets, the flexible resources should focus on them. Since prices in those markets are usually very volatile and can reach considerably high prices in case of energy scarcity, the flexibility sources should be able to retrieve their investment cost by taking part in the intraday and balancing markets. These new flexibility sources are presented and characterized in the following chapter.

3. NEW SOURCES OF FLEXIBILITY

In close-to-fully-renewable power systems, there is no traditional controllable generation from gas, oil or coal power plants. Instead, bulk electricity is produced by variable renewable energy sources, primarily wind and solar. Thus, the burden on balancing the system has been fully transferred to hydro power plants with accumulation and renewable thermal power plants, such as biogas and biomass. However, such energy sources are generally limited and cannot satisfy the entire need for flexibility. Bearing this in mind, there are two options for increasing the flexibility. The first one is energy storage that can charge when there is excess electricity in the system, and discharge when the system lacks electricity. The second option is assigning (a part) of the balancing burden to the consumers. Although certain technologies can be used both as a bulk energy storage and at the consumers' premises, the following subsections discuss these two options individually.

3.1. Bulk Energy Storage

Currently, a vast majority of bulk energy storage in power systems is in the form of pumped hydro power plants. This technology is mature with sufficient roundtrip efficiency (app. 70%), and well represented worldwide. However, it strongly depends on the geographical conditions and requires major environmental interventions.

A recent storage technology that has a potential of being used in bulk is battery storage. Although lithium-ion battery storage owes its attractiveness and declining prices to the rollout of electric vehicles, some rather specific battery types are installed exclusively as stationary battery storage. For example, sodium-sulphur (NaS) batteries 7.2 h discharge rate make them ideal for energy-intensive services. The overall installed NaS power capacity in the world in 2016 was 365 MW. The largest installation of this storage technology is the one in Italy by the Italian transmission system operator Terna, with 34.8 MW [10].

Nevertheless, the most widely used battery technology today is lithium-ion, including a number of sub-technologies, e.g. with cobalt (LCO), nickel-cobalt- aluminum-oxide (NCA, NCR), nickel-manganese-cobalt-oxide (NMC, CGR, INR), manganese-oxide, (LMO) and ferro-phosphate (LFP, IFR). The world's largest lithium-ion battery is the one in Hornsdale Power Reserve in South Australia, with the capacity of 150 MW/193.5 MWh [11].

Lithium-ion battery storage has some very good characteristics. First, it has very high roundtrip efficiency, ranging from 80% to over 90%. Secondly, it responds instantaneously, making it suitable for very fast services. Thirdly, the degradation rate is fair, as usually lithium-ion batteries can perform a couple of thousand cycles before displaying a significant loss of capacity (20% or more of the initial capacity). Generally, they are highly reliable, but are known to perform badly at low temperatures. Additionally, the investment cost of these batteries is still quite high, which requires very elaborate business models and stacking of multiple services [12]. Generally, energy arbitrage is insufficient for achieving the required return-on-investment [13]. In order to achieve higher profits, it is required for battery storage to take part in the reserve markets. A model for optimal dispatching of lithium-ion battery energy storage in pay-as-bid secondary reserve market is presented in [14], while a joint participation of battery energy storage in the energy and reserve market was investigated in [15], [16].

3.2. Flexible Consumers

Moving the burden of power system balancing to the consumers is possible due to controllability of the demand and inclusion of power generation and energy storage at the consumers' premises, which is in line with the Fourth Energy Package known as Clean Energy for All Europeans [17].

Flexible industrial facilities can drain their flexibility from the industry process itself. Generally, pumps, ventilators, compressors, heating and cooling systems, dryers and mills can all defer their consumption in time and take part in demand response.

The US Department of Energy defines demand response as *changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized* [18]. If such facilities comprise controllable power generators, e.g. biogas power plant, or variable generation combined with battery storage, e.g. rooftop solar plant combined with battery storage, their flexibility potential is even greater. An energy use breakdown for cement industry is presented in [19]. Such analysis can serve as a great stepping stone for determining the potential of an industry facility in providing demand response. An example of an investment of industrial facilities in battery storage and photovoltaics for participation in energy markets is available in [20].

Commercial buildings have a strong potential for demand response too, mostly because of the thermostatically controlled loads, e.g. electric heating, boilers and air conditioning. An interested reader may find a comprehensive introduction to demand response control strategies in commercial buildings in [21]. A model for optimal investment of a hotel in battery storage is available in [22].

Finally, the residential sector also possesses a strong demand response potential. However, this potential is very difficult and very expensive to put in service, as the devices have rather low power capacity. This increases the cost of demand-response-ready investments, makes the measurements difficult to obtain and, consequently, reduces the economic impact of demand response. Furthermore, the perception of demand response among residential consumers is not always positive [23]. Some of the household devices with a high potential for demand response include clothes washers and dryers, air conditioners, water heaters, ovens, dishwashers and refrigerators [24]. Additionally, if many households on a specific location contain swimming pools, e.g. Florida in the USA, pool pumps can be utilized to provide demand response as well [25].

Lately, due to a serious uptake of electric vehicles, electric vehicle charging stations have been identified as a major flexibility source. An increasing number of electric vehicles can have an adverse effect on the power stability if inadequately controlled, but if the charging process is controlled in a system-aware way, they can become a valuable flexible asset. Controlled electric vehicle charging can bring high benefits to the balancing of the power system due to the electric vehicles' high storage capability [26] and availability during the day [27]. Essentially, electric vehicles are batteries whose primary aim is to serve the drivers' needs. However, they are not connected to the charging stations at all times, which reduces their availability to act according to the power system's needs. Since their battery capacity and (dis)charging power capacity is rather low as compared to the overall system needs, they are commonly aggregated by a special entity, i.e. an aggregator that distributes the control commands to the electric vehicles, and acts in the energy and/or reserve market as one entity representing a number of electric vehicles or charging stations [28].

4. MATHEMATICAL MODEL FOR NEW FLEXIBILITY SOURCES

This section presents mathematical models for new sources of uncertainty identified in the previous section – battery storage, representing both stationary storage and electric vehicle battery storage, and thermostatically controlled loads as the most common representative of the demand response devices.

4.1. Battery Storage

Battery storage models are built upon the generic storage model presented below:

$$p_t^{\mathrm{ch}} \leq P \tag{13}$$

$$p_t^{\mathrm{dis}} \leq P \tag{14}$$

$$soe_t = soe_{t-1} + p_t^{\mathrm{ch}} \cdot \eta^{\mathrm{ch}} - p_t^{\mathrm{dis}} / \eta^{\mathrm{dis}} \tag{15}$$

$$soe_t \leq SOE \tag{16}$$

Constraints (13) and (14) limit the energy storage charging power p^{ch}, which is the power taken from the grid, and the discharging power, p^{ch}, which is the power injected into the grid. State-of-energy in each time step soe_t is calculated in (15) based on the state-of-energy in the previous time step, electricity taken from the grid multiplied with the charging efficiency η^{ch}, and electricity injected into the grid, accounting for the discharge efficiency η^{dis}. Finally, constraints (16) limits the state-of-energy of energy storage.

The generic energy storage model (13)–(16) has been widely used in the literature as the battery storage model. For instance, in [29], the authors use the generic battery storage model to optimize their deployment in a unit commitment model to reduce congestion and, consequently, reduce the system operation costs. In [30], the batteries are used in a security-constrained optimal power flow model to deal with contingencies. In the microgrid investment model presented in [31], as well as in the microgrid bidding model in [32], batteries are modeled using the generic energy storage model (13)–(16). Even when modeling the batteries in electric vehicles, the generic energy storage model is predominantly used for modeling, see e.g. [33], [34], [35]. However, the generic energy storage model does not accurately capture the behavior of the lithium-ion batteries, which were directly or indirectly considered in the papers above. Figures 3–5 show voltage, current and power characteristics during charging for C-rate[1] levels 0.2C, 0.5C and 1C, while Figures 6–8 show the same curves for the discharging process. All the curves were captured in the SmartGrid Lab at the University of Zagreb, Faculty of Electrical Engineering and Computing [36].

The battery charging voltage curves in Figure 3 show that the battery voltage increases as the battery is charged. Comparing these curves with the corresponding ones in Figure 2 clearly shows that the charging process has two phases. In the first phase, the charging currents is constant (constant-current phase), and the voltage increases steeply. After the voltage reaches the upper threshold, the current needs to be reduced in order to avoid further increase of voltage and damage to the battery (the upper voltage threshold is set based on the battery producer's datasheet). This is known as the constant-voltage phase. Figure 3 shows the charging power, which is the most relevant quantity for power system economics models. It is obtained as a multiplication of voltage and current. One can notice that the charging power at the beginning, i.e. at low state-of-energy, slowly increases due to increase in voltage (the current is constant), but after entering the constant-voltage phase, the charging power is abruptly reduced due to the depreciation of the charging current. This is why battery charging at 1C lasts for 2.5 hours, as can be seen in Figure 1–3, instead of one hour. For the same reason, charging at 0.5C lasts three instead of two hours, while charging at 0.2C lasts six instead of five hours.

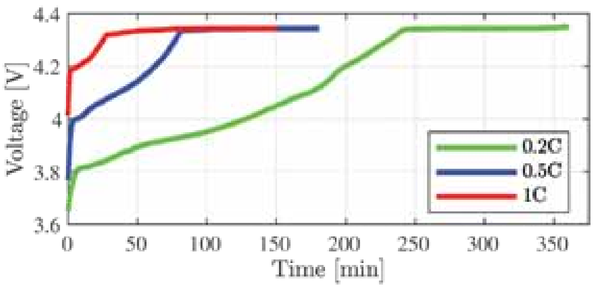

Figure 3. Charging voltage of a lithium-ion battery for three charging speeds.

Slika 3. Napon punjenja litij-ionske baterije za tri brzine punjenja

1 C-rate is a theoretical measure of the speed at which a battery is charged or discharged. For example, 1C discharge rate would deliver the battery's rated capacity in 1 hour, 0.5C in 2 hours, etc.

The discharging voltage in Figure 4 is reduced as the battery is discharged. However, the discharging current in Figure 5 is constant throughout the discharging process, resulting in almost flat discharging power shown in Figure 6. The presented laboratory tests indicate that the generic energy storage model (13)–(16) fails to capture the fact that the battery charging ability is reduced with its state-of-energy. More specifically, constraint (13) does not properly capture the physico-chemical properties of lithium-ion batteries. In literature, however, there are two linear battery models that quite accurately capture this fact; more information can be found in [37], [38].

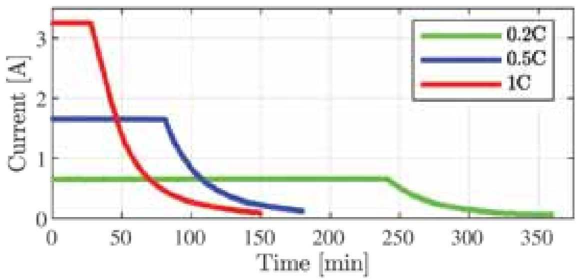

Figure 4. Charging current of a lithium-ion battery for three charging speeds.

Slika 4. Struja punjenja litij-ionske baterije za tri brzine punjenja

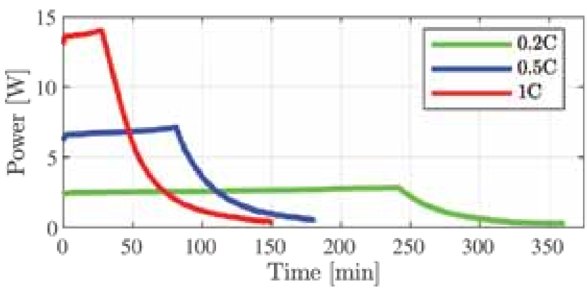

Figure 5. Charging power of a lithium-ion battery for three charging speeds.

Slika 5. Snaga punjenja litij-ionske baterije za tri brzine punjenja

4.2 Thermostatically Controlled Loads

A credible representative of thermostatically controlled loads, whose model is presented below, is a heat pump (HP) with an auxiliary heating (AH) device. These are used to provide both the space heating (SH) and hot water (HW).

$$d_t = p_t^{\mathrm{HP,SH}} + p_t^{\mathrm{HP,HW}} + p_t^{\mathrm{AH,SH}} + p_t^{\mathrm{AH,HW}} \tag{17}$$

$$p_t^{\mathrm{HP,SH}} + p_t^{\mathrm{HP,HW}} \leq P^{\mathrm{HP}} \tag{18}$$

$$p_t^{\mathrm{AH,SH}} + p_t^{\mathrm{AH,HW}} \leq P^{\mathrm{AH}} \tag{19}$$

$$\dot{q}_t^{\mathrm{SH}} = k^{\mathrm{SH}} \cdot p_t^{\mathrm{HP,SH}} + k^{\mathrm{SH}} \cdot p_t^{\mathrm{AH,SH}} \tag{20}$$

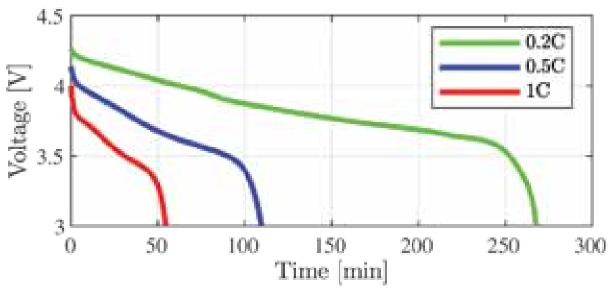

Figure 6. Discharging voltage of a lithium-ion battery for three discharging speeds.

Slika 6. Napon pražnjenja litij-ionske baterije za tri brzine pražnjenja.

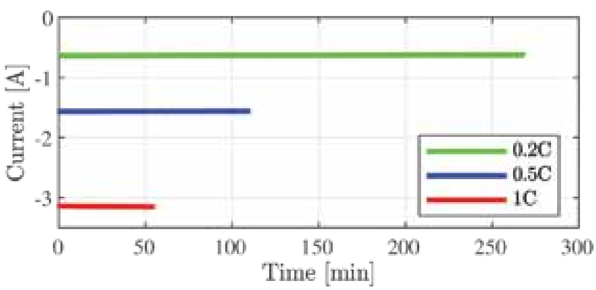

Figure 7. Discharging current of a lithium-ion battery for three discharging speeds.

Slika 7. Struja praznjenja litij-ionske baterije za tri brzine pražnjenja.

The power balance equation (17) determines the overall power demand d_t required for supplying the heat pump for space heating $p_t^{HP,SH}$ and hot water $p_t^{HP,HW}$, as well as supplying the auxiliary heating device for space heating $p_t^{AH,SH}$ and hot water $p_t^{AH,HW}$. The maximum power capacities of the heat pump P^{HP} and the auxiliary heating device P^{AH} are enforced in (18) and (19). Constraint (20) translates the electrical power consumed by the heat pump and the auxiliary heating devices to the required thermal power for space heating $\dot{q}_t^{SH}$ using the space heating performance coefficient k^{SH}. Equation (21) calculates the indoor temperature based on the temperature in the previous time step, heating power $\dot{q}_t^{SH}$ and thermal losses and solar gains $C_{p,t}^{SH}$. Coefficient matrices A_p^{SH} and B_p^{SH} are matrices of the linear state-space model used to simulate the indoor thermal behavior. Constraint (22) sets the upper $T_{p,t}^{SH,hi}$ and lower $T_{p,t}^{SH,lo}$ limits on the indoor temperature the inmates find comfortable. Constraints (23)–(25) model the hot water utilization in the same way constraints (20)–(22) model the space heating. Additional explanations on the model can be found in [39], [40].

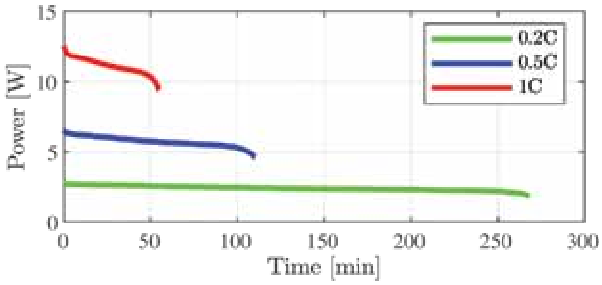

Figure 8. Discharging power of a lithium-ion battery for three discharging speeds.

Slika 8. Snaga pražnjenja litij-ionske baterije za tri brzine pražnjenja.

5. CONCLUSION

The aim of this paper was to point out the increasing needs for flexibility in modern power systems with high capacity from variable renewable sources. The technical perspective calls for new sources of flexibility in the form of deferrable loads and battery storage, both stationary and electric vehicles, whose goal is to take part in the balancing of the power systems. The paper identifies some major obstacles for a strong rollout of such devices:

1. The price of both the devices able to defer their consumption and battery storage is still rather high, and the benefits these devices bring to an investor can as yet not justify their cost. This is especially the case with countries such as Croatia, where electricity prices for consumers are relatively low (see the takeaways from [20]).
2. Control of a large number of distributed devices is not only expensive, but prone to security breaches. This is especially the case with publicly available charging stations [41]. Their high power capacity makes tampering with control systems of the electric vehicle charging stations dangerous for the power system security [42].
3. Further improvements in modeling of flexible resources is needed. This includes variable efficiency of the battery charging and discharging process (depending on the charging and discharging currents), as well as improved modeling of specific household devices with a potential for demand response.
4. Market structures need to be further developed in order to enable trading closer to real time and reward flexible sources. A good example of such market is the flexiramp product in California [8].

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FLEKSIBILNOST ELEKTROENERGETSKIH SUSTAVA

Sažetak

Moderni elektroenergetski sustavi oslanjaju se na proizvodnju električne energije iz obnovljivih izvora energije, prvenstveno vjetra i Sunca. Međutim, nepravilnost i promjenjivost njihove proizvodnje električne energije uzrokuje povećane zahtjeve za fleksibilnošću sustava. Nadalje, uslijed prestanka rada konvencionalnih termalnih elektrana, koje su i same bile izvor fleksibilnosti, nedostatak iste sve je više izražen. Stoga su potrebni novi izvori fleksibilnosti. Članak izučava stvarne primjere povećanih zahtijeva za fleksibilnošću, identificira nove izvore fleksibilnosti (baterije i odaziv potrošnje), te predstavlja relevantne matematičke modele i daje preporuke za buduća istraživanja u ovom području.

Ključne riječi: fleksibilnosti; obnovljivi izvori energije; baterijski spremnici energije, termostatski upravljana trošila.

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