Abstract—This paper examines the revenue potentials of frequency control provision (primary and secondary control) by flexible unit portfolios, also referred to as Virtual Power Plants (VPPs), consisting of generators, energy storage units, and controllable thermal loads. A unified modeling approach for power system units, referred to as “Power Nodes modeling approach”, is introduced and used for setting up an optimization-based control strategy. Time simulations over parameter ranges are undertaken so as to determine the control potential provided by two benchmark portfolios. Ancillary service market data from Switzerland is used to assess the value of using energy-storing units for frequency control instead of generators only. This yields a quantitative evaluation of the commercial potential of control services by coordinated flexible unit portfolios.

Index Terms—Demand Response, Energy Storage, Virtual Power Plants, Ancillary Services, Frequency Control

I. INTRODUCTION

The increasing amount of renewable energy in-feeds in many countries leads to a variability of power generation on seasonal over weekly and daily down to sub-hourly time frames [1], [2]. While the seasonal and daily variations need to be accounted for by backup generation and/or energy storage, the hourly to sub-hourly variations, along with the limited predictability of the in-feeds, call for enhanced balancing mechanisms and additional active-power reserves. In the context of “Smart Grid” research and implementation efforts, the participation of energy storage and demand response in short-term control of the active power balance is a major point of discussion [3].

Energy storage provides an attractive, yet still fairly expensive option for short-term control actions. The main advantages lie in the short response times of many storage technologies such as pumped-hydro, battery and compressed-air energy storage (CAES) systems compared to large thermal generation units, and the ability to replace conventional reserves which are expensive due to the opportunity cost arising from not being able to use a given unit for power production. A major challenge is the dynamically evolving storage level (state of charge, SOC) which is subject to stringent constraints. This requires the explicit consideration of SOC and constraints in the dispatch and control algorithms.

Additional control potential lies in the inherent flexibility of thermal loads. Direct control of thermostatically controlled appliance populations, enabled by a suitable communication system, allows the integration into balancing and frequency control mechanisms [4], [5]. In certain areas, existing communication infrastructure for direct load control, nowadays mostly used for peak shaving and load shifting, can be taken advantage of, provided that the control performance is sufficient.

A crucial question for the implementation of ancillary service provision schemes is the revenue that can be achieved with a certain power provision on ancillary service markets. Previous work on the value of controllable demand has been done mainly for load shifting and the exploitation of price differences, such as presented in [6]. The value of energy storage devices for short-term dispatch and balancing was assessed in [7]. Frequency control ancillary service provision by Plug-In Hybrid Electric Vehicles (PHEVs) was described and economically evaluated in [8], demonstrating substantial revenue potentials.

The splitting of control signals among generators and storage devices has been discussed before. For instance, in [9] it is proposed to split the control signal by using frequency filters. This allows the distribution of the high-frequency components to the storage units and the low-frequency components to the generation units. The approach is implementable with relative ease and very transparent with respect to its effects. However, it lacks the possibility to base the splitting directly on economic criteria, to conduct the splitting optimally in that sense, and to react on-line to changing operating conditions. The present work explicitly addresses these issues.

In this paper, we examine a market-based approach to ancillary service provision by flexible unit portfolios consisting of storage, controllable load, and generation units. In this setup, individual market players, called aggregators, assume control of unit populations in order to provide ancillary services. The aggregators can both be separated from or incorporated in established electricity utilities. The main point of investigation is the contribution that a certain type of unit can make to a control product. This requires a consideration of the inherent energy constraints that any kind of storage unit exhibits (acceptable internal temperature range in the case of thermal loads). This question is approached similarly to [10] by a time simulation setup utilizing benchmark portfolios described in a previously developed modeling framework called “Power Nodes” [11], [12]. The results of the time-domain simulations are merged with an analysis of historical price data, in this case taken from the Swiss ancillary service market for control reserves, in order to estimate the financial revenue potential of a given unit portfolio bidding into the market.
A. Power Node Model with Storage

For the purpose of this paper, we will use the affine power node model as presented in [11]. The dynamics of a power node $i \in \mathcal{N} = \{1, \ldots, N\}$ is described by:

$$
C_i \dot{x}_i = \eta_{\text{load},i} u_{\text{load},i} - \eta_{\text{gen},i}^{-1} u_{\text{gen},i} + \xi_i - w_i - a_i (x_i - x_{ss,i}),
$$

where $a_i$ is a constant loss factor governing the state-dependent losses and $x_{ss,i}$ is a constant offset which corresponds to the thermal equilibrium in the case of heat storage units. The equation is subject to the operational constraints

$$
\begin{align}
(a) \quad 0 \leq x_{i,\min}^i \leq x_i \leq x_{i,\max}^i \leq 1, \\
(b) \quad 0 \leq u_{\text{gen},i} \leq u_{\text{max},i}, \\
(c) \quad 0 \leq u_{\text{load},i} \leq u_{\text{max},i}, \\
(d) \quad \dot{u}_{\text{gen},i} \leq u_{\text{max},i}, \\
(e) \quad \dot{u}_{\text{load},i} \leq u_{\text{max},i}.
\end{align}
$$

B. Power Node Model without Storage

Power nodes are also useful to represent processes independent of energy storage, such as intermittent renewable generation or conventional generation and load. A process without storage implies an algebraic coupling between the instantaneous quantities $\xi_i, w_i, u_{\text{gen},i}$, and $u_{\text{load},i}$; storage-dependent loss does not exist ($v_i = 0$). Equation (1) degenerates to

$$
\xi_i - w_i = \eta_{\text{gen},i}^{-1} u_{\text{gen},i} - \eta_{\text{load},i} u_{\text{load},i}.
$$

The constraints on the power quantities (2)(b)–(e) hold in the same way. The model is particularly relevant for external supply and demand processes which are not directly controllable, while there may be a choice to curtail the process. Examples are intermittent power generation ($\xi_{\text{drv},i}(t) \geq 0$) and classical load ($\xi_{\text{drv},i}(t) \leq 0$).

C. Absolute and Relative Coordinates

Since the provision of control services is based on deviating from a scheduled working point (sch), the power node equation needs to be transformed to relative coordinates ($\Delta$) for the purpose of this paper. This is achieved by applying the transformation ($\cdot$) = ($\cdot$)$^{\text{sch}} + \Delta(\cdot)$. Equation (1) and (3) in the $\Delta(\cdot)$-case are:

$$
\begin{align}
C_i \Delta \dot{x}_i &= \eta_{\text{load},i} \Delta u_{\text{load},i} - \eta_{\text{gen},i}^{-1} \Delta u_{\text{gen},i} + \Delta \xi_i - \Delta w_i - a_i \Delta x_i, \\
\Delta \xi_i - \Delta w_i &= \eta_{\text{gen},i}^{-1} \Delta u_{\text{gen},i} - \eta_{\text{load},i} \Delta u_{\text{load},i}.
\end{align}
$$

The constraints (2)(a)–(e) have to be transformed accordingly.

III. UNIT PARAMETERIZATIONS

In this section, we develop parameter and constraint sets for a number of common power system units in the power node nomenclature. These will be used to assemble benchmark unit portfolios for the study of control service provision. Cost function terms are also derived which are as much as possible based on literature values of operational cost for the respective units.
A. Thermal Generation

1) Power Node Equation and Constraints: Thermal generators rely on a chemically stored primary energy source, such as natural gas, biomass, or coal. The conversion process can be controlled such that the primary energy input and the electric energy output, coupled by the generator’s efficiency, can be freely determined within a certain range. Ramping constraints exist due to physical limitations of the combustion process and the thermo-mechanical cycle. The power node equation reads

\[ u_{\text{gen}} = \eta_{\text{gen}} \xi \]  

subject to

\[ 0 \leq u_{\text{min}} \leq u_{\text{gen}} \leq u_{\text{max}} \]  
\[ \dot{u}_{\text{gen}} \leq \frac{\pi_{\text{ss}}}{2} \] .

2) Cost Function: In the simplified case of a constant generator efficiency, the fuel cost can be expressed as a linear term in the primary energy input \( \xi = \eta_{\text{gen}}^{-1} u_{\text{gen}} \). The cost for operation and maintenance (O&M) of the generator is linear as well. The cost function \( J_{\text{gen}} \) reads thus:

\[ J_{\text{gen}} = (\pi_{\text{fuel}} \eta_{\text{gen}}^{-1} + \pi_{\text{O&M}}) u_{\text{gen}} \]  

where \( \pi_{\text{fuel}} \) is the fuel price and \( \pi_{\text{O&M}} \) is the cost for Operation and Maintenance of the plant per produced unit of energy.

Start-up and shut-down costs are neglected in the context of this work. Depending on the type of power plant, significant additional costs can be incurred by ramping the power plant up and down for load-following, balancing, or frequency control. According to [13], the ramping cost can be represented by a quadratic cost term, here expressed in a continuous-time framework:

\[ \pi_{\text{ramp}}^2 \dot{u}_{\text{gen}} \]  

where the power derivative is penalized quadratically, multiplied by the specific ramping cost \( \pi_{\text{ramp}} \).

B. Battery Storage

1) Power Node Equation and Constraints: The battery energy storage system (BESS) is modeled as an energy-storing power node with in-feed and load term and a certain efficiency. Note that the charge and discharge management of a real BESS requires a detailed modeling of the physical battery properties, e.g. its internal temperature [14]. However, we believe that a system-level dispatch and control strategy should be agnostic to these local parameters, which makes a power node representation useful for representing the battery towards the power system. In this case, unmodeled internal dynamics can be taken care of by updates of parameters and state variables. The power node equation reads

\[ C \dot{x} = \eta_{\text{load}} u_{\text{load}} - \eta_{\text{gen}}^{-1} u_{\text{gen}} - v \]  

subject to the constraints

\[ 0 \leq x_{\text{min}} \leq x \leq x_{\text{max}} \leq 1 \]  
\[ 0 \leq u_{\text{min}} \leq u_{\text{gen}} \leq u_{\text{max}} \]  
\[ 0 \leq u_{\text{load}} \leq \eta_{\text{load}} \leq u_{\text{max}} \] .

The term \( v \geq 0 \) may contain a physical model for the stand-by losses through self-discharge but is set to zero in this work. As most batteries are suitable for fast ramping [15], a ramping constraint is omitted.

2) Cost Function: The operating costs of batteries are caused by limited lifetime (expressed in number of charge/discharge cycles) and investment cost. For control service provision, it is useful to attribute this cost \( \pi_{\text{bat}} \) to both charge and discharge since both imply a utilization of the control resource:

\[ J_{\text{bat}} = \frac{\pi_{\text{bat}}}{2} u_{\text{gen}} + \frac{\pi_{\text{bat}}}{2} u_{\text{load}} \]  

C. Aggregated Electric Water Heaters

1) Power Node Equation and Constraints: The aggregated group of electric water heaters possesses the ability to modulate its consumption but cannot feed energy back into the grid. The energy stored in the device population is subject to constraints due to the necessity to provide hot water to the customers. For shortness, the derivation of the power node equation is omitted here. The model of an individual water heater is based on a heat balance of the tank, which is subject to water draws, thermal losses, and heat input through the heating element. The interested reader is referred to [16] for details. It is assumed that an underlying coordination algorithm, such as presented in [17], takes care of distributing the control action onto the individual appliances of the water heater population. This allows to describe the coordinated population in an aggregate form using just one differential equation. In the power node equation, the heat loss is modeled by the term \( a(x - x_{\text{ss}}) \), where \( a \) is a loss coefficient and \( x_{\text{ss}} \) is the thermal equilibrium with the ambiance, while water draws are modeled by the variable \( \xi \leq 0 \). The power node equation reads

\[ C \dot{x} = \eta_{\text{load}} u_{\text{load}} - a(x - x_{\text{ss}}) + \xi \]  

subject to the constraints

\[ 0 \leq x_{\text{min}} \leq x \leq x_{\text{max}} \leq 1 \]  
\[ 0 \leq u_{\text{load}} \leq u_{\text{max}} \]  
\[ \xi \leq \xi_{\text{drv}} \]  
\[ \xi_{\text{drv}}(t) \leq 0 \] .

Since the population is assumed to be tightly controlled with respect to its aggregate power, a modeling of energy payback behavior or the so-called cold load pick-up (CLPU) [18] is not necessary.

2) Cost Function: The cost function of the electric water heater aggregation shall represent the need to supply the customers with hot water while maintaining control flexibility. This is mapped into a heuristic state penalty \( \pi_{\text{EWH}} \) on the deviation from a defined SOC level (here equal to 0.5):

\[ J_{\text{EWH}} = \pi_{\text{EWH}}(x - 0.5)^2 \]  

D. Definition of Auxiliary Power Nodes

For the formulation of certain control objectives, it is useful to define two specific types of power nodes, which we will refer to as “control power node” and “slack power node”. The control power node is needed to model the effect of external control signals that influence the power node portfolio, while the slack power node provides a representation of a power source or sink that is not part of the considered unit portfolio, but still needs to be included. The control power node is needed to model the effect of external control signals that influence the power node. We will refer to this as “control power node” and “slack power node”. The slack power node provides a representation of a power source or sink that is not part of the considered unit portfolio, but still needs to be included in the control problem. Both control and slack power nodes do not possess inherent storage ($C_{\text{ctrl}} = 0, C_{\text{slack}} = 0$). The defining equations are

$$
\xi_{\text{ctrl}} = u_{\text{ctrl}} - u_{\text{load}}, \quad \xi_{\text{slack}} = \eta_{\text{slack}} - u_{\text{gen}} - \eta_{\text{load}} u_{\text{load}}.
$$

As the slack power node represents external physical generation and consumption, the efficiencies are included in the equation. It can be subject to power and ramping constraints. The control power node, however, is a purely virtual entity and thus does not possess efficiencies nor constraints. It is driven by the external process

$$
\xi_{\text{ctrl}} = \xi_{\text{drv}}(t),
$$

where $\xi_{\text{drv}}(t)$ represents the time series of the external control signal. The control power node is particularly useful in the relative formulation:

$$
\Delta \xi_{\text{ctrl}} = \Delta u_{\text{gen}} - \Delta u_{\text{load}}, \quad \Delta \xi_{\text{ctrl}} = \Delta \xi_{\text{drv}}(t).
$$

The auxiliary power nodes enter into the power node portfolio as additional optimization variables subject to the equality constraints from equation (16)–(20).

E. Benchmark Portfolios

Two benchmark portfolios are defined which will be used in the numerical simulations. The first one consists of a battery storage and a generator, and the second one of an electric water heater aggregation and a generator. More complex portfolio compositions are not considered in this paper since the analysis of the interaction between the individual units would become too extensive. We rather attempt to identify key characteristics of frequency control provision by energy-storing units. Table I sums up the parameter sets of the two portfolios. Variations of certain parameters will be conducted within the case study, which will be explained later on.

IV. CONTROL STRATEGY

In this section, we present a control strategy based on model predictive control (MPC) which enables a portfolio of units, represented by power nodes, to follow an externally imposed control signal. The control signal is distributed on the different units by an optimization algorithm executed in a receding horizon fashion. Since the control problem involves dynamic states and inter-temporal constraints, a look-ahead optimization has to be used. However, control signals in frequency control are not known in advance and can only be predicted roughly, either by simple assumption of persistence of the current value or according to typical patterns during the day [19]. Therefore, we use a prediction horizon of just two steps. For simplicity, we assume the prediction to be perfect.

As a firm commitment to following the control signal is made when a bid placed in the ancillary service market is accepted by the TSO, we will put priority on highly reliable signal tracking. However, we shall allow for deviation from the signal in order to avoid infeasibility of the optimization problem in case of too stringent constraints. In the following, we will explain the control setup, the “endogenous” cost function reflecting the cost incurred by control action in the portfolio, and an additional cost term imposed through the control objective.

A. Optimization Setup

Figure 2 shows the general setup of the control strategy applied to the power node portfolio extended by the two auxiliary power nodes defined above. The discrete-time control signal $\xi_{\text{ctrl}}(k)$ enters the portfolio via the control power node. The active power balance in $\Delta$-quantities is the principal constraint that forces the power node portfolio to track the control signal with its aggregate power setpoint deviation. The power balance is established between in-feeds and out-feed into and out of a single-bus grid, i.e., the control system is oblivious to grid topology. This is a realistic assumption in the ENTSO-E [20] area, where all frequency control actions (except for tertiary control in some cases) do not take into account the grid constraints. The slack power node allows to fulfill the power balance if the regular portfolio is unable to do so.

B. Endogenous Cost in Absolute and Relative Coordinates

For including the power node system in the optimization, all equations are converted to discrete time. In order to make the notation more compact, we define the state and input variable vectors for the dynamic state variables $x_{\text{state}}$ with $i_{\text{dyn}} \in \{N \mid C_i > 0\} = 1, \ldots, N_{\text{state}}$, and $u_{\text{gen},i}, u_{\text{load},i}, \xi_i$, and $w_i$ with $i \in N = 1, \ldots, N$:

$$
x = [x_1, \ldots, x_{N_{\text{state}}}]^T, \quad u = [u_{\text{gen},1}, \ldots, u_{\text{gen},N}, u_{\text{load},1}, \ldots, u_{\text{load},N},
\xi_1, \ldots, \xi_N, w_1, \ldots, w_N]^T.
$$
The cost arising from operating the power node portfolio can be formulated in terms of absolute quantities or in terms of relative (\(\Delta\)) quantities. In absolute quantities, we consider the following cost function for an individual time step \(k\):

\[
J_{\text{endo}}(k) = (x(k) - x^{\text{ref}})^T Q (x(k) - x^{\text{ref}}) + q^T (x(k) - x^{\text{ref}}) + (u(k) - u^{\text{ref}})^T R (u(k) - u^{\text{ref}}) + \delta u^T(\delta R \delta u(k))
\]

(23)

Here, \(x^{\text{ref}}\) and \(u^{\text{ref}}\) are constant references which serve to penalize the deviation from a desired base value (equal to zero in most cases), \(\delta u(k) = u(k) - u(k-1)\) is the deviation from one time step to the other, \(Q, R,\) and \(\delta R\) are quadratic cost matrices, and \(q\) and \(r\) are cost vectors. The endogenous cost function for the relative model formulation (deviation from schedule \(\Delta(\cdot) = (\cdot) - (\cdot)^{\text{sch}}\)) is given as

\[
J_{\text{endo}}^{\text{rel}}(k) = \Delta x^T(k)Q \Delta x(k) + (2(u^{\text{sch}}(k) - u^{\text{ref}})^T Q + q^T)\Delta x(k)
\]

(24)

\[
+ \Delta u^T(k) R \Delta u(k) + (2(u^{\text{sch}}(k) - u^{\text{ref}})^T R + r^T) u(k)
\]

\[
+ \Delta \delta u^T(k) \delta R \Delta \delta u(k) + 2 \delta u^{\text{sch}}(k) \delta R \Delta \delta u(k)
\]

These cost functions enable the description of cost incurred within the power node portfolio in both absolute and relative coordinates. We will use the power node equations in \(\Delta\)-quantities, and thus the relative endogenous cost function, for the frequency control problem.

C. Control Signal Tracking

The tracking of the control signal is achieved by imposing the power balance constraint over all \(N+2\) power nodes (including slack and control power node) in \(\Delta\)-quantities:

\[
\sum_{i=1}^{N+2} (\Delta u_{\text{gen},i}^*(l) - \Delta u_{\text{load},i}^*(l)) = 0
\]

(25)

for every step \(l\) of the prediction (denoted by the asterisk). Note that we will omit the generation cost of the generator in our optimization problem, since the net reduction or increase of the production is either insignificant (primary control) or compensated by the control energy payments as explained in Section V-C.

The control signal itself enters the problem via the control power node, which is simply

\[
\Delta u_{\text{ctrl}}^{\text{load}} = -\Delta \xi^{\text{ctrl}}
\]

(26)

Since imposing the control signal as an equality constraint onto the system may lead to infeasibility of the optimization, it is practical to allow for a deviation from the control signal by introducing a virtual slack power node that may cover some of the control action:

\[
\Delta u_{\text{gen}}^{\text{slack}} = \Delta \xi^{\text{slack}}
\]

(27)

As a deviation from the control signal should only be a last resort to avoid infeasibility, we will penalize the slack contribution quadratically in the cost function with a penalty factor \(\pi_{\text{dev}}\) which should be chosen very high in comparison with the other cost terms. The cost function for frequency control is then as follows:

\[
J(k) = \sum_{l=1}^{k+N_{\text{set}}} \left( J_{\text{endo}}^{\text{rel}}(l) + \pi_{\text{dev}} t_s (\Delta u_{\text{gen}}^{\text{slack}}(l))^2 \right)
\]

(28)

where \(t_s\) is the sampling time. The presented setup allows us to track, and deviate from, control signals that are imposed on the portfolio. In what follows, we will discuss the details of using the setup with primary and secondary frequency control signals.

D. Primary Frequency Control

Primary frequency control is a proportional control which adapts the power production of a unit (usually a generation unit) based on the frequency deviation from its set value. The negative inverse of the proportionality factor between frequency deviation and power change is referred to as droop [21], here denoted by \(S\). It can be expressed as

\[
S = -\frac{\Delta f}{\Delta P} = \frac{f_{\text{p.u.}}}{P_{\text{p.u.}} S_B}
\]

(29)

where \(\Delta f = f - f_{\text{set}}\) is the system frequency deviation, \(\Delta P = P - P_{\text{set}}\) is the deviation from the power production setpoint, p.u. denotes per-unit values, \(S_B\) is the apparent power base of the system, and \(f_{\text{set}}\) is the frequency setpoint. In the ENTSO-E [20], the droop has to be set such that the entire primary frequency reserve is activated at a frequency deviation of ±200 mHz. This means that for a control band of 1 MW, the system frequency deviation must be multiplied by 1 MW/0.2 Hz = 5 MW Hz to derive the control signal. Furthermore, a dead-band of ±20 mHz is imposed where no control action shall be taken, so the system frequency must be pre-processed accordingly. We will refer to the measured frequency deviation with the
filtered-out deadband as $\Delta f_{\text{db}}(k)$. The control signal input to the power node portfolio scaled by the offered primary control capacity $\hat{P}_{\text{prim}}$, presented in (26), is thus bound to the input signal

$$\Delta \xi_{\text{ctrl}} = \frac{\hat{P}_{\text{prim}}}{200 \text{ mHz}} \Delta f_{\text{db}}(k) \quad (30)$$

\[E. \text{ Secondary Frequency Control}\]

Secondary frequency control is a proportional-integral (PI) control loop on the control area level. It is responsible for keeping the system frequency at its nominal value and for maintaining the scheduled tie-line exchanges with other control areas on an integral basis. Due to the integrating part, there can only be one central controller per control area, since several integrating controllers acting on the power balance of the system can lead to destabilizing effects. The control signal is derived from the Area Control Error [21] and is issued in percent of the secondary control band:

$$\Delta \xi_{\text{ctrl}} = -\hat{P}_{\text{LFC}} Y(k) \quad (31)$$

with $Y \in [-100\%, 100\%]$ being the secondary control signal in percent and $\hat{P}_{\text{LFC}}$ being the offered secondary frequency control capacity.

V. Simulation Study

In the following, we conduct a simulation study to evaluate the frequency control approach using the benchmark portfolios defined in Section III-E. We define simulation scenarios which shall enable an illustration and evaluation of the benefits arising from using energy storage for ancillary services.

A. Simulation Scenarios

In order to quantify the benefits of energy storage for primary and secondary frequency control, we take the following approach: Real system frequency and secondary frequency control signal data (available in 10-second resolution over the time span of one month) is scaled to a benchmark control band of $\hat{P} = \pm 10$ MW. This is a realistic bid size in many ancillary service markets and it is useful for easy comparison. We will simulate the system over the time span of 30 days with variations in power and energy capacity of the units. In particular, we are interested in the share of the control band that an energy-storing unit (storage device or thermal load) can securely account for, which provides a measure for the value of using the combination of units instead of the generator alone. The following parameters are varied: 1) the share $\alpha$ of the control band that is covered by the energy-storing unit (defining its rated power), while the generator control band is scaled to $1 - \alpha$, and 2) the storage capacity of the energy-storing unit, measured in hours of charging at rated power disregarding the efficiency. The simulation scenario parameter sets are described in Table II. Note that we use the MATLAB-like notation “Start:StepSize:End” for defining the parameter variation.

B. Numerical Results

In order to illustrate the behavior of the optimization-based control system, Fig. 3 shows a time simulation of Portfolio A (battery and generator) providing secondary control reserves. It can be seen that the battery is mainly used for the peaks of the signal since charging and discharging the battery incurs cost and energy losses.

Now we conduct the parameter variations described above in order to assess the value of the joint reserve provision. The following quantities are of interest for the performance evaluation: 1) contribution of the slack generator, providing a measure for deviation from the control signal, 2) net operating profit arising from the combination of generator and energy-storing unit, and 3) change of net operating profit compared with using only a generator for control. Figure 4 shows these properties for (top to bottom) primary control with Portfolio B, secondary control with Portfolio A, and secondary control with Portfolio B. The net profit calculation is based on the economic evaluation framework which we introduce next.

C. Economic Evaluation

For the economic evaluation of the simulation results, price data from Switzerland is used. First, we introduce the compensation schemes for primary and secondary control provision as defined in [22]. Table III displays the most important assumptions affecting the economic evaluation.

1) Primary Control: Primary control is compensated by a capacity fee per MW of control band provided for a certain time span. Bids can only be placed symmetrically. Currently, the auctions take place once a week. Energy compensation is not used since system frequency deviation is relatively symmetrical and does not exhibit longer deviations from zero.

Figure 3. Time simulation of Portfolio A providing secondary control

<table>
<thead>
<tr>
<th>Parameter variations for frequency control assessment</th>
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<tr>
<td>Energy cap. C/Δu_{\text{max}} [h] [1, 2.5, 5, 7.5, 10]</td>
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</tbody>
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<table>
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<tr>
<th>Assumptions for economic parameters</th>
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<tr>
<td>Spot market price and control signals January 2009</td>
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<tr>
<td>Fuel price for generator 40 EUR/MWh</td>
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<tr>
<td>Capacity price Primary Control 30 EUR/(MW-h)</td>
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<td>Capacity price Secondary Control 30 EUR/(MW-h)</td>
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</table>
2) **Secondary Control**: Secondary control is compensated by a capacity fee and an energy fee. While the capacity price per MW of control band provided for a certain time span is determined by the auction process, the energy price follows a fixed scheme: The control energy is averaged over a time slice of 15 minutes and paid for with an hourly spot market price including a bonus of ±20%. In case of a generation increase (or load decrease), the ancillary service provider receives the spot price +20%, in case of a generation decrease (or load increase) he pays the spot price −20%. In order to smoothen price spikes, the provider’s revenue is floored by the weekly base price and his costs are capped by the weekly base price.

3) **Net Operating Profit**: We evaluate the maximum net profit that can be made (under the idealistic assumption of perfect bidding) by using the combined portfolio to provide ancillary services. To calculate the operating profit \( \Pi \) [EUR], we use the following formula:

\[
\Pi = R_{\text{capa}} + R_{\text{en.net}} - C_{\text{strg}} - C_{\text{ramp}} - \Delta C_{\text{fuel}} - C_{\text{opp}}, \tag{32}
\]

where \( R_{\text{capa}} \) [EUR] is the capacity revenue of the ancillary service provision, \( R_{\text{en.net}} \) [EUR] is the net control energy revenue, \( C_{\text{strg}} \) [EUR] are storage cycling costs, \( C_{\text{ramp}} \) [EUR] are ramping costs of the generator, \( \Delta C_{\text{fuel}} \) [EUR] is the change in fuel cost through the ancillary service provision compared to a constant setpoint, and \( C_{\text{opp}} \) [EUR] is the opportunity cost incurred by not using the generator control band for energy production. The individual revenue and cost terms are defined as follows:

\[
R_{\text{capa}} = \pi_{\text{capa}} T_{\text{prov}} P_{\text{prov}}, \tag{33}
\]

with the control reserve capacity price \( \pi_{\text{capa}} \) [EUR/MW], the duration of reserve provision \( T_{\text{prov}} \) and the provided symmetrical power control band of width \( P_{\text{prov}} \). The following term describes the energy revenue (secondary control):

\[
R_{\text{en.net}} = \sum_{t_{\text{MTU}}=1}^{T_{\text{MTU}}} 1.2 \pi_{\text{spot}}^{\text{capped}}(t_{\text{MTU}}) E_{\text{net}}^{\text{feed-in}}(t_{\text{MTU}}) - \sum_{t_{\text{MTU}}=1}^{T_{\text{MTU}}} 0.8 \pi_{\text{spot}}^{\text{capped}}(t_{\text{MTU}}) E_{\text{net}}^{\text{cons}}(t_{\text{MTU}}), \tag{34}
\]

with the capped and floored spot prices \( \pi_{\text{spot}}^{\text{capped}} \) and \( \pi_{\text{spot}}^{\text{floored}} \) and with the fed-in or consumed control energy (netted over market time units \( T_{\text{MTU}} = 1, \ldots, T_{\text{MTU}} \) of 15 minutes) \( E_{\text{net}}^{\text{feed-in}} \) and \( E_{\text{net}}^{\text{cons}} \). Describing the storage cycling cost for all time steps \( k = 1, \ldots, k_{\text{max}} \) straight-forward:

\[
C_{\text{strg}} = \sum_{k=1}^{k_{\text{max}}} \left( \frac{1}{2} \pi_{\text{bat}} \Delta u_{\text{bat}}^{\text{gen}}(k) + \frac{1}{2} \pi_{\text{bat}} \Delta u_{\text{load}}^{\text{bat}}(k) \right) t_s, \tag{35}
\]

where \( t_s \) is the sampling time of the problem. The ramping cost is equal to

\[
C_{\text{ramp}} = \sum_{k=1}^{k_{\text{max}}} \frac{\pi_{\text{ramp}}}{t_s} (\Delta u_{\text{gen}}^{\text{gen}}(k) - \Delta u_{\text{gen}}^{\text{gen}}(k - 1))^2, \tag{36}
\]

and the change in fuel cost is equal to

\[
\Delta C_{\text{fuel}} = \sum_{k=1}^{k_{\text{max}}} \Delta u_{\text{gen}}^{\text{gen}}(k) \pi_{\text{fuel}} t_s. \tag{37}
\]

The opportunity cost of the generator is caused by not being able to produce at full capacity when \( \pi_{\text{spot}} > \pi_{\text{fuel}} \), and having to produce more than its minimum when \( \pi_{\text{spot}} < \pi_{\text{fuel}} \). This can be described by:

\[
C_{\text{opp}} = \sum_{k=1}^{k_{\text{max}}} (1 - \alpha) t_s P_{\text{prov}} \cdot |\pi_{\text{spot}}(k) - \pi_{\text{fuel}}(k)|. \tag{38}
\]
D. Discussion of the Results

The results displayed in Fig. 4 give an indication as to how the control quality and the revenue of ancillary service provision are affected when using joint portfolios instead of generators only. In the left column of Fig. 4, one can observe that the most deviation from the control signal (here depicted in the form of normalized Root-Mean-Square-Error, RMSE) is incurred for high storage power shares above 50% both for the battery and the water heaters\(^1\). The permissible control signal deviation may be restricted in practice, so the evaluation of the deviation percentage allows for an appropriate sizing of the portfolio in accordance with legislative frameworks. The revenue of the combined portfolios is displayed for the simulation time span of 30 days in the center column of Fig. 4, and compared to the base case (ancillary service provision by generator only) in the right column. One can see a revenue increase of 50–75% for storage shares of 60% where the control signal deviation is still relatively small. For batteries, larger shares than 70% do not bring about additional benefits due to the cycling. For a water heater share of 90%, the revenue is increased by 90 – 110%.

VI. CONCLUSIONS

We have demonstrated in this paper how energy-storing units such as storage devices and controllable thermal loads can participate in frequency control services in conjunction with generators. An optimization-based control strategy is useful to distribute the control actions in an economically optimal way and to honor state constraints. We find that the simulation-based sizing of the storage units for frequency control is a promising approach since it takes into account time series properties such as the energy contained in the signal and deviations from zero. The simulated scenarios show that the combination of generators and energy-storing units yields a substantial net operating profit increase, which may be used to amortize the investment in the joint portfolio. For a real deployment of the described control systems, further investigations of the storage level management over time, accurate modeling of battery degradation, and ancillary service bidding strategies are necessary.

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REFERENCES


\(^1\) Note that the sizing of the water heater population is somewhat conservative since a symmetrical control band around the mean electricity consumption was chosen. Due to the relatively low duty cycle, the significant amount of roughly 1,000 to 21,000 4-kW water heaters (depending on the desired control band share) was considered.


