Towards an Optimal Activation Pattern of Tertiary Control Reserves in the Power System of Switzerland

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Abstract—This paper focuses on designing a framework for the activation of tertiary control reserves in order to improve frequency control performance. Considering the fact that tertiary control reserves are not immediately available and, therefore, must be requested in advance, a pattern is proposed based on a Model Predictive Control (MPC) scheme. Linear regression models based on a robust Maximum Likelihood Estimate (MLE) are employed to predict the control signal. The proposed optimization technique is simulated using measurements from the Swiss power system to illustrate technical and economic aspects.

I. INTRODUCTION

The successful operation of interconnected power systems requires the balance of electricity generation and consumption. Power imbalances cause frequency deviations that can lead to equipment damage and even blackouts. Hence, balancing power deviations is important and performed by frequency control schemes. Frequency control represents an important part of ancillary services and can schematically be decomposed into frequency containment, frequency restoration and reserve replacement. In Continental Europe the Transmission System Operators (TSOs) bear responsibility for frequency control and the respective control processes are known as primary, secondary, and tertiary control [14]. First, primary control stabilizes frequency within some seconds over the interconnected areas and independent of the fault’s geographical location. Primary control acts as a proportional controller that avoids high frequency deviations. Due to the proportional structure of primary control, a steady-state error is unavoidable. Next, secondary control, also called Load Frequency Control (LFC) or Automatic Generation Control (AGC), brings the frequency back to its nominal value and restores scheduled power interchanges to their nominal values. A linear combination of the frequency deviation and tie-line power is known as Area Control Error (ACE). Secondary control is a proportional integrator that regulates the ACE to zero. It automatically reacts to deviations occurring in its own area within a time varying from several seconds to some minutes. Finally, tertiary control assumes a complementary role to secondary control reserves. In the event of persistent deviations and in order to free up secondary control reserves, the dispatcher manually activates tertiary control reserves based on his experience. The required reaction time varies from 15 minutes to several hours [10, Section 2], [1, Sections 3 and 4], [14], [15]. Figure 1 illustrates the reaction time frame for the different control reserves. The associated products of these reserves, mostly procured on a market basis, may vary from country to country [15].

To activate tertiary control reserves, the dispatcher takes into account that tertiary control power is available with a time-delay, known as activation or reaction time, and is delivered to the power system for a certain duration, called operating time. Operating time describes the minimum time that a generating unit must feed power into the grid (see Figure 2); thus, a reserve cannot be requested for a time interval less than its operating time. If a TSO aims at compensating power imbalances by tertiary control power, the interval over which the forecast error is calculated cannot be shorter than the total of the operating and activation time of the reserves called upon. For instance, in Germany, the forecast of wind energy generation has a day-ahead basis; therefore, there is generally an error between actual and forecast values that is compensated by tertiary control reserves [12]. There is, however, no common framework for the activation of tertiary control reserves referring to the UCTE Operation Handbook [14].

The frequent activation of tertiary control reserves relieves secondary control reserves, and hence, increases the security of power systems. In addition, manual reserves generally cost less than automatic reserves. Implementing a pattern for regular activation of tertiary control reserves may be economically beneficial. Therefore, a framework for tertiary control reserves activation is of interest to TSOs from both technical and economic point of views.

![Figure 1](image-url)  
Fig. 1. Frequency control after a fault event; indicated timescales are standard values taken from [14].

This paper presents an activation pattern for tertiary control reserves based on a Model Predictive Control (MPC)
scheme. MPC is employed since the non-negligible activation time of the respective reserves necessitates a predictive pattern. MPC generates a sequence of control decisions by solving a constrained finite time optimal control problem. The first control decision is applied on the system, then, new measurements are sampled and the process is repeated for the next step [13]. The LFC problem was addressed as an application of modern optimal control theorems in [8]. The concept of using MPC for LFC was introduced in [6], where a distributed MPC controller coordinates the generator outputs by determining set points to the turbine controllers. A decentralized MPC strategy for the LFC problem was proposed in [2]. In [18], the concept of an ancillary service manager was developed based on MPC.

The main contribution of this paper is to introduce a predictive activation pattern for tertiary control reserves considering the reaction time of the respective reserves. Linear regression models predict the required control power over a finite horizon. Two approaches are proposed: a location model and an autoregressive (AR) process. Robust MLE estimates the model parameters. The predicted control signal assumes the role of the trajectory followed by the MPC control decision. MPC takes the properties of available tertiary control reserves, such as activation prices, into consideration to synthesize the control decision.

The paper is organized as follows. Section II presents the location model and the AR process as models predicting the control signal. A background on MLE is provided for the estimation of model parameters. The MPC scheme and formulation of a tertiary control reserve activation pattern based on MPC are given in Section III. Section IV provides the simulation of the proposed pattern using measurements from the Swiss power system. Finally, Section V is devoted to conclusions and perspectives.

II. SYSTEM DESCRIPTION AND MATHEMATICAL MODEL

Investigations on frequency control necessitates a model describing power systems dynamics. In this section, we first present the frequency dynamic model. Then, a location model and an AR process based on a robust MLE are provided. Finally, we define criteria to measure the goodness of the regression models.

A. Dynamic Model of Power Systems

The model, shown in Figure 3, describes the frequency dynamics of power systems. It illustrates the dynamical behavior of power systems when disturbances occur in the grid. A short description of this dynamic model is presented in the following (see [1, Section 2] for more details).

Generator dynamics are described by the swing equation as follows:

\[ \Delta \dot{f} = \frac{f_0}{2H S_B} \Delta (P_m - \Delta P_e) \quad , \]

where \( f_0 \) is the pre-disturbance frequency. The indices \( e \) and \( m \) stand for electrical and mechanical power, respectively. \( S_B \) and \( H \) denote the rating of the machine and the inertia constant, respectively.

Load dynamics comprises two groups of frequency-dependent and frequency-independent loads. Frequency-dependent loads are described by:

\[ \Delta P_{\text{load}}^f = \frac{1}{D_f} \Delta f + \frac{2W_0}{f_0} \Delta \dot{f} \quad . \]

The values of \( W_0 \) and \( D_f \) are highly dependent on the structure of the load and are, in general case, time-variant.

The tie-line power deviation between areas \( i \) and \( j \) is:

\[ \Delta P_{ij} = \hat{P}_{T_{ij}}(\Delta \varphi_i - \Delta \varphi_j) \quad , \]

where \( \hat{P}_{T_{ij}} = \frac{U_i U_j}{X} \cos(\varphi_{ij} - \varphi_{ij}) \).

Since \( \Delta \varphi_i = \omega_i t + \Delta \varphi_i \), one derives:

\[ \Delta \dot{P}_{ij} = 2\pi \hat{P}_{T_{ij}}(\Delta f_i - \Delta f_j) \quad . \]

Turbine dynamics are usually assumed to have a first-order transfer function in power system studies, however, the type of turbine dynamics significantly affects the control performance of power systems. For example, a hydro turbine whose transfer function has a non-minimum phase behavior [7], [1, Section 3]. Therefore, an accurate model describing turbine dynamics is crucial.

\[ \frac{1}{D_p} \Delta P_{\text{cond},f} = \Delta P_{\text{load},f} - \Delta P_{\text{cond},m} - \Delta P_{\text{load},m} + \Delta P_{\text{TLC}} \quad . \]

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\[ \Delta f_t = \frac{f_0}{2H \omega_s} \Delta P_{\text{load},f} \quad . \]

\[ \Delta P_{\text{cond},f} = \Delta P_{\text{load},f} - \Delta P_{\text{cond},m} - \Delta P_{\text{load},m} + \Delta P_{\text{TLC}} \quad . \]

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\[ \Delta f_t = \frac{f_0}{2H \omega_s} \Delta P_{\text{load},f} \quad . \]
the frequency dynamic model can be simplified depending on the timescale of the control schemes as will be described in Section III.

B. Linear Regression Models

The availability of a data profile of the control signal motivates modeling based on linear regression models.

1) Location Model: Equation (5) describes the location model [11], where the outcome of \( y \) depends on an unknown parameter of \( \mu \) and a random error of \( \omega \):

\[
y_t = \mu + \omega_t \quad (5)
\]

The terms \( \omega_1, \omega_2, \ldots, \omega_n \) are independent replications of the same process and have the same distribution function \( F_0 \). The goal is to estimate \( \mu \) when the observations of \( y_1, \ldots, y_n \) are available. To this end, the likelihood function of \( \mu \), given in (6) where \( f_0 \) denotes joint distribution of observations, is maximized as in (7).

\[
L(y_1, \ldots, y_n; \mu) = \prod_{i=1}^{n} f_0(y_i - \mu), \quad (6)
\]

\[
\hat{\mu} = \arg \max_{\mu} L(y_1, \ldots, y_n; \mu) \quad (7)
\]

Since \( f_0 \) is positive, one can write

\[
\hat{\mu} = \arg \min_{\mu} \sum_{i=1}^{n} \rho(y_i - \mu),
\]

where \( \rho = -\log f_0 \), and arrives at the following implication:

\[
\sum_{i=1}^{n} \psi(y_i - \hat{\mu}) = 0, \quad \psi := \frac{d\rho}{d\mu}.
\]

The term \( \psi \) is called influence function, since it shows the influence of a single measurement on the parameters estimation [9], [11]. The MLE minimizes a function of residuals, \( \rho \), derived based on the distribution of the data. Thus, the MLE solution highly depends on the choice of cost function \( \rho \) and, consequently, \( \psi \). If the distribution were known, the MLE would result in the optimal solution in the sense of achieving the lowest possible asymptotic variance among a class of estimates. The distribution is, however, unknown; fitting a true distribution to the observations requires a very large sample set; particularly, the regions with fewer data, such as tails, heavily influence the result.

A data profile usually contains data behaving atypically, known as outliers. In power systems, any type of disturbance that saturates the control reserves can be defined as an outlier. In addition, erroneous measurements and the durations over which the TSO performs a test on the power system are other examples of outliers. A robust estimate is insensitive to small changes of all observations and large changes in a few of them. As previously mentioned, the influence function \( \psi \) is a useful measure of robustness. Outliers have a large distorting influence on the parameter estimation if the \( \psi \) function is not robust enough in the presence of outliers. To assure that an estimate is robust, the respective influence function should be continuous and bounded [3]. From several robust functions that have been published, those from Huber, Logistic, and Fair are presented in the following [3].

a) Huber Function:

\[
\psi_H(y) = \begin{cases} 
-K & y < -K \\
-K \leq y \leq K \\
K & y > K 
\end{cases},
\]

where \( K \) stands for a constant value. A large value of \( K \) corresponds to a normal distribution while a lower value is more prone to a Laplace distribution.

b) Logistic Function: One may figure out the Logistic function, corresponding to a Logistic distribution, as a Huber function without discontinuities at \( y = \pm K \).

\[
\psi_L(y) = K \tanh \left( \frac{y}{K} \right),
\]

where \( K \) denotes a constant value.

c) Fair Function: The least absolute residuals, corresponding to a Laplace distribution, is less influenced by outliers compared to the least squares method. The reason is that the influence function of the least absolute estimate is bounded whereas that of the least squares method is not. The following equations present \( \rho \) and \( \psi \) functions of the least absolute estimate:

\[
\rho(y) = |y|, \quad \psi(y) = \begin{cases} 
-1 & y < 0 \\
1 & y > 0 
\end{cases}.
\]

Although the influence function is bounded, it is discontinuous at zero. In order to have a continuous function, the Fair function is defined according to

\[
\psi_F(y) = \frac{y}{1 + |y|}.
\]

The functions presented are all convex, and hence, converge to a global optimum solution. Additionally, they are bounded, continuous, and appropriate for a robust estimate.

2) Autoregressive Model: The second approach is to derive an AR model based on the data profile of the control signal. An AR model of order \( p \), \( AR(p) \), presents the current value of a series as a linear function of its own past values as described by

\[
y(t) = \alpha_0 + \alpha_1 y(t-1) + \alpha_2 y(t-2) + \ldots + \alpha_p y(t-p) + \nu_t, \quad (8)
\]

where the innovations \( \nu_t \) are independent and identically distributed (i.i.d.) random variables with mean 0 and finite variance \( \sigma^2 \). The term \( \alpha_0 + \alpha_1 y(t-1) + \alpha_2 y(t-2) + \ldots + \alpha_p y(t-p) \) stands for the forecast value of \( y(t) \) if there is a strong autocorrelation between the measurements. Thus, the first step to develop an AR model is to measure the autocorrelation of the sample data.

a) Autocorrelation: The linear correlation of the data of a time series is known as an autocorrelation presented by (9). The autocorrelation measures the predictability of a series at point \( t \) based on its value at time \( s \):

\[
\rho(s, t) = \frac{\gamma(s, t)}{\sqrt{\gamma(s, s) \gamma(t, t)}}, \quad (9)
\]

where \( \gamma(s, t) \) denotes the covariance of the sample data of time \( t \) and \( s \). The autocorrelation has a value between \( -1 \) and 1. If there exists a strong autocorrelation between the data, then, the absolute value of autocorrelation is close to 1 while a weak autocorrelation yields a value close to 0.
b) Order Selection: The next step to derive an AR model is to decide on the order of the model, namely p. An arbitrary long order causes a redundancy of the parameters and consequently the over-fitting problem, whereas a small order may yield an inaccurate model. The trade-off between complexity and accuracy is addressed by the Akaike Information Criterion (AIC). Akaike suggested balancing the error of a fit against the number of parameters to measure the goodness of a fit. Equation (10) presents the AIC [16, Section 2], [11, Section 8].

\[
AIC = \ln \sigma_p^2 + \frac{n + 2p}{n},
\]

where \(\sigma_p\) denotes a function of residuals and \(n\) is the total number of observations. The value of \(p\) corresponding to minimized AIC specifies the best order of the model. A robust method to estimate \(\sigma_p\) is to down-weight the large residuals of outliers.

c) Parameters Estimation: The conventional way to estimate the model parameters \(\alpha_0, \alpha_1, \ldots, \alpha_p\) is to minimize the least squares residuals \(r := Y - \hat{\alpha}X\), where

\[
X := \begin{bmatrix}
y_p & y_{p-1} & \cdots & y_1 \\
y_{p+1} & y_p & \cdots & y_2 \\
\vdots & \vdots & \ddots & \vdots \\
y_{t-1} & y_{t-2} & \cdots & y_{t-p} \\
y_t 
\end{bmatrix}, \quad Y := \begin{bmatrix}
y_{p+1} \\
y_{p+2} \\
\vdots \\
y_t 
\end{bmatrix}
\]

represent an AR process as in (8). This leads to

\[
\hat{\alpha}_{LS} = \arg \min_{\alpha} \sum_i (r_i)^2 = (X^T X)^{-1} X^T Y.
\]

Since the influence function, \(\psi(y) = y\), is not bounded, the least squares method is not robust. A robust MLE minimizes a bounded function of the residuals according to

\[
\hat{\alpha}_{MLE} = \arg \min_{\alpha} \sum_i \rho(r_i).
\]

Note that the sample data for a certain point in time is the value of the control signal at this time over the last \(D\) days. This means the estimate of control signal at time \(t\) on day \(d\) is independent of the control signal at time \(t-1\) on the same day, but depends on the measurements at time \(t\) over days \(d-1, d-2, \ldots, d-D\). A further step is to cluster the data into week and weekend days, since the control signal value slightly decreases over the weekends. This means that if a weekday estimation is desired, the mean value is computed over the last \(D\) weekdays, and if the current day is a Saturday or a Sunday, then the average is calculated over the last \(D\) weekend days. A large number for \(D\) means more sample data, and consequently, more precise results.

3) Goodness of Fit and Technical Criteria: A conventional way to measure the accuracy of a forecast model is to calculate Mean Absolute Percentage Error (MAPE), given in (11). The MAPE is a robust performance index since it is computed over some days, however, it has a drawback if the actual value is zero.

\[
MAPE = \frac{100}{d} \sum_{i=1}^{d} \frac{|y_i - \hat{y}_i|}{y_i},
\]

where \(d\), \(y\), and \(\hat{y}\) denote the duration of forecast, actual, and predicted values, respectively.

Although there are other measures based on a scale of the error to evaluate the accuracy of fits, they would not be suitable for the forecast of the control signal. The reason is illustrated in the following example. Consider a scenario, where 100 MW control power is required for the upcoming time instant. If the forecast value is 10 MW, then the error of 90% indicates a so-called weak forecast. But, the application of tertiary control reserve activation pattern presents a practical aspect. That is, the TSO activates 10 MW tertiary control reserves based on the weak forecast, and hence, the secondary control is deployed 10 MW less than a scenario without tertiary control reserves activation. Therefore, technical criteria are defined to measure the goodness of the models presented. These criteria are introduced to compare the models in the sense of improving frequency control performance.

a) Saturation occurrences: In Switzerland, secondary control reserves are dimensioned based on the controllability of the power system 99.9% of time [4]. This means a deficit of secondary control reserves at 0.1% of time is allowed that is shared by positive and negative secondary control reserves. If a large imbalance occurs such that the secondary control reserve meets its limits, it is defined as saturation. According to this deficit rate, saturation is allowed to occur for about 10 hours per year, although, this limit is not always met in practice. Two criteria can be defined based on the controllability of the power system. First, how the saturation is affected by implementing the different approaches defined. Second, if the new resulting saturation satisfies the desired deficit rate.

b) Decrease in daily peaks: The other criterion to evaluate the performance of the proposed models is to measure their impact on the daily peaks of the control signal. The peaks of the control signal are important since they may cause the saturation of the secondary control reserves and jeopardize the system security. To this end, the positive and negative peaks of the real control signal are compared to respective peaks after applying the activation patterns. If peaks are reduced, this is considered to be good result.

III. MODEL PREDICTIVE CONTROL SCHEME

A. Optimal Control Problem

The essence of MPC, also known as Receding Horizon Control (RHC), is to synthesize the control decision sequences by solving an open-loop optimal control problem over a given finite horizon, i.e. finite-time optimal control. The first control input in the sequence is applied on the plant and then the optimal control problem is resolved based on new measurements for a time horizon shifted one step forward. Repeatedly solving the open-loop optimization,
while updating with new state measurements, makes MPC a closed-loop control strategy. MPC is a good choice for activation of tertiary control reserves as it has both optimal and predictive control features. Furthermore, changes in the operating conditions, such as new tertiary control reserves with shorter operation time or time-variant sources, can be implemented in an MPC setup by defining additional constraints.

MPC optimizes forecasts of system behavior accomplished with a process model, thus, the model plays a significant role. State-space notation is commonly used to present a linear time-invariant (LTI) model. Equation (12) presents such an LTI system subjected to input and state constraints $H_u$ and $H_s$.

$$
x(k + 1) = A x(k) + B u(k)$$

$$y(k) = C x(k) + D u(k)$$

$$s.t. \begin{cases} H_f^T x(k) \leq 0^T, & k = 0, \ldots, N \\
H_u^T u(k) \leq 0^T, & k = 0, \ldots, N - 1 \end{cases}$$

where $A \in \mathbb{R}^{nxn}$ and $B \in \mathbb{R}^{nxm}$ are dynamics and input matrixes, respectively, $x \in \mathbb{R}^n$ denotes system state and $u \in \mathbb{R}^m$ is the control input.

$$x(k) = \begin{bmatrix} \Delta f \\ \Delta P_{ij} \end{bmatrix}$$

and $u(k) := \Delta P_m - \Delta P_{load}$ describe the system in Figure 3. The slow dynamics of the system, caused by the timescale of tertiary control, implies $\Delta P_{ij} \approx 0$ and $\Delta f \approx 0$, i.e. $x(k+1) = 0$. Since the control policy $u(k)$ compensates power imbalances, the system equation is simplified as follows:

$$0 = \begin{bmatrix} \frac{1}{T_f} & -1 \\ 1_{2x2} & 0_{1x2} \end{bmatrix} x(k) + \begin{bmatrix} \alpha \end{bmatrix} u(k)$$

$$y(k) = \begin{bmatrix} 1_{2x1} & 0_{1x2} \end{bmatrix} x(k) + \begin{bmatrix} 0 \end{bmatrix} u(k) .$$

The standard MPC formulation is as follows:

$$\min_u \sum_{k=0}^{N-1} ||Q x(k)||_L + ||R u(k)||_L$$

$$s.t. \begin{cases} x(0) = x(0) \\
 x(k + 1) = A x(k) + B u(k) \\
 H_f^T x(k) \leq 0^T, & k = 0, \ldots, N \\
 H_u^T u(k) \leq 0^T, & k = 0, \ldots, N - 1 \end{cases}$$

where weighting matrixes $Q = \text{rank}(n)$, $R = \text{rank}(m)$, and norm $L \in [1, \infty)$. $N$ denotes the prediction horizon [6], [13].

**B. Tertiary Control Reserves Activation based on MPC**

The regression model predicts the required control signal over a forecast horizon $N$. The MPC controller dispatches the required power forecasted from the available tertiary control reserves, represented by different offers in the daily ancillary services market. Therefore, the predicted control signal assumes the role of a trajectory which has to be followed by available tertiary control reserves. The tertiary control energy bids are characterized by size, i.e. their amount of power, price, and N-1 security criterion. Note that the Swiss TSO cannot request only a part of a reserve bid [5], [17]. For example, if the control power of 15 MW is required and a bid with size of 16 MW is available, the TSO cannot request 15 MW out of 16 MW. If a bid is called, then, its total capacity is available after 15 minutes. This means the decision variables only take the value 1 or 0 representing the acceptance or refusal of a bid, respectively. Therefore, the optimization problem is an integer programming problem. MPC chooses the bids such that the required control power is satisfied with the lowest possible cost. The bids from generating units in areas where an outage or a contingency problem exists, such as some nodes in the south of Switzerland over the summer, are penalized and, consequently, not chosen. The contingency is represented by a normalized value. If the normalized value is more than 1, there is a contingency problem associated with the respective bid. If the geographical location of the generating unit of a bid is available, the N-1 contingency analysis of the respective bid can be determined.

The generating units participating in tertiary control prefer not to be activated for a short time, thus, a reserve that has already been activated gets a higher priority when other conditions, like bid price and bid size, are equal.

The following MPC setup is selected to activate tertiary control reserves considering the desired performance.

$$\alpha^* = \arg \min_{\alpha} \sum_{k=0}^{N-1} ||Q (P^{ref}_c - \alpha^T(k) u(k))||_1 + \sum_{k=0}^{N-1} ||R \alpha(k)||_1$$

$$+ \sum_{k=0}^{N-1} ||S(\alpha(k+1) - \alpha(k))||_1$$

$$s.t. \begin{cases} \|P^{ref}_c - \alpha^T(k) u(k)||_1 \leq \Delta P_L \\
P^{ref}_c = [P^{ref}_c(k = 0), \ldots, P^{ref}_c(k = N - 1)]^T \\
u_i(k) = u_i^b \\
\alpha \in \{0, 1\} \}$$

where $P^{ref}_c$ is estimated by a linear regression as aforementioned. $Q$, $R$, and $S$ are weighting matrixes. In this study, the weight matrix $R$ is determined based on the prices of the bids and indexes of the system security and contingency. $u_i^b$ stands for block sizes. $\Delta P_L$ denotes the limits on overcompensation, i.e. how much the total power of bids is allowed to exceed $P^{ref}_c$. The dispatcher decides for this value; here $\Delta P_L = 5$ MW is chosen as it is the smallest bid size in the Swiss ancillary services market [17].

**IV. SIMULATION RESULTS**

This section provides the simulation results of applying the proposed technique on real measurements of the Swiss power system over a period of 6 months (October 2010 to March 2011). First, the different proposed models are compared
based on the technical criteria defined. Next, the operating
time of tertiary control reserves is analyzed to evaluate the
effectiveness of different operating time for tertiary control
reserves. Finally, the economic aspects of this pattern are
provided.

A. Time for Tertiary Control Reserves Activation

To apply the framework proposed, the TSO requires to
know the optimal time to request tertiary control reserves;
that is, when tertiary control power should be available in the
power system. Analysis of the control signal, from October
2010 to March 2011, illustrates a trend during specific hours
over a day. As illustrated in Figure 4, the median of the
control signal over different months follows a downward
trend during the first four hours of a day, followed by,
an upward behavior from 5:00 to 12:00. The trend then
decreases downward until 18:00. There is no consistent shape
over the period of 18:00 to 21:00, but a downward trend
is observed again towards the final hours of the day. The
peaks occurring at the full hours are a consequence of the
hourly products of the European power market [19]. The
power plants schedules change at the full hours following
a step-wise operation whereas the loads have a continuous
behavior. These differences cause high frequency deviations
and, consequently, peaks in the control signal.

The detected trend implies that the value of the control
signal at each time instant partly results from a stochastic
process and is partly determined by a deterministic process.
In other words, the behavior of the control signal within a
specific time interval indicates that the secondary controller
is stimulated by regularly occurring events in the power
system at these times. Hence, tertiary control power can
compensate for the deterministic part of the control signal.

The minimum operating time of tertiary control reserves
is 15 minutes; therefore, the control signal is predicted over
a time interval of 15 minutes. This results in a trajectory;
tertiary control power is activated to keep the deviation of the
predicted trajectory close to zero. Note that tertiary control
reserves do not provide power in a trajectory shape, but
the control power is available in step-shaped blocks (see
Figure 2). To keep the deviations of control power around
zero, the amount of tertiary control power that should be
requested is the average of the minimum and maximum
of the trajectory predicted. If the interval over which the acti-
vation amount of the control power is calculated comprises
the converse values such that they cancel each other out,
the activation amount is zero or close to zero. Therefore, an
interval containing sharp changes of the control signal is not
recommended. For instance, an interval including a full-hour
is not recommended since the control signal has a converse
trend before and after a full hour referring to Figure 4. This
leads to the selection of two intervals of 15 minutes before
and after the full hours. Two intervals of 15 minutes can
also be specified before and after half hours. Thus, tertiary
control power should be available at the quarter-hours which
corresponds to the schedule interval, describing the minimum
time interval that Balance Responsible Parties (BRP) can
announce new schedules to the TSO. The MPC scheme is
simulated assuming different functions \( \psi \) for the internal
model. A cost function which fits to the distribution of the
data leads to a good estimation. One may consider fitting
a distribution to the observations instead of trying out the
different \( \psi \) functions, representing the different distributions.
The lack of data to find a true distribution makes this idea
impractical.

B. Decrease in Peaks and Saturations

As previously mentioned, if the peaks of the control signal
and saturations decrease, there are more free secondary
control reserves available. This increases the security of the
power system. Figure 5 demonstrates the decrease in
daily peaks and saturations in blue and red respectively as
percentage of time for the different regression models. The
positive and negative peaks of the actual control signal are
compared to respective peaks after applying the activation
patterns over aforesaid duration. For instance, 66 % means
that the peaks decreases 66 % of time over a duration
of 6 months. This statement stands for the decrease in
saturations as well. Referring to Figure 5, one can deduce
that the Fair function, corresponding to the median of the
data, performs best. Furthermore, the location models have
a better performance compared to the AR models. The reason
is that there is no strong autocorrelation between the control
signal of the consecutive days, thus, the performance of the
AR process is not as good as the location model. An
example of the autocorrelation of the control signal data
is illustrated in Figure 6. The sample data is the control
signal over an interval from 9:30 to 10:30 on October 9
and 10, 2010. Figure 7 depicts the actual control signal of
November 22, 2010 in red and the same signal simulated
using the MPC strategy in blue as an example. The negative
and positive peaks decrease by 10 %. Additionally, the MPC
strategy avoids the saturations occurring at 7:00 and 17:00,
and reduces the required secondary control energy by 25%.

C. From an Economic Point of View

Sharing the control task of secondary with tertiary control power changes the energy flow and, consequently, procurement costs. According to Figure 8, the proposed pattern decreases the control energy costs by about 30% over the aforesaid duration of 6 months, however, this trend is not consistent in each month. The negative cost indicates the payment to the TSO. The frequent activation of tertiary control reserves might influence the market prices. Note that the energy price is not only a function of demand, but also affected by other factors such as operational limits and generation fixed costs. Hence, the market influence should be studied in an independent work. The other economic aspect is related to the deficit rate. A decrease in deficit rate means more security of supply and less inadvertent exchange, which implicitly translates to economic savings. Applying the activation pattern reduces the deficit rate by 45% over the 6 months considered. Figure 9 illustrates the density function of the control power with and without the activation pattern. One can infer that occurrence of the positive secondary control reserve saturation, namely 400 MW, is significantly reduced by applying the activation pattern. The secondary control reserves can be sized based on the new deficit rate. This means that the Swiss TSO could have reduced the power provision of secondary control reserves by up to 70 MW and still have maintained the same deficit rate during the aforementioned 6 months. The power provision of negative secondary control reserves is not affected since the negative saturations result mostly from re-dispatch procedures with neighboring TSOs. Since it occurs randomly, the location estimator cannot predict it.

D. Operating Time of Tertiary Control Reserves

The pattern has thus far been simulated assuming an operating time of 15 minutes. It is of interest to evaluate the performance of the reserves with different operating time. Different operating times can be interpreted as different market products. Shorter operating time provides more flexibility and accuracy. Figures 10 and 11 show that for a longer operating time, the performance in terms of decrease in daily peak values and saturations deteriorates. However, even an operating time of 1 hour improves frequency control performance compared to the current situation. Since the technical performance of a scenario with operating time of 30 minutes does not differ from the one with operating time of 15 minutes, tertiary control reserves can be requested based on 30 minutes operating time. This satisfies tertiary control power providers who are willing to be requested for a longer horizon. Figure 12 depicts the costs associated with different operating time over different months. Note that the cost is not a monotonic function of the operating time; a scenario in which the operating time is 60 minutes costs less than those with the operating time of 15 and 30 minutes. One can conclude from Figures 10, 11, and 12 that tertiary control reserve saturation, namely 400 MW, is significantly reduced by applying the activation pattern.
control reserves with operating time of 5 or 10 minutes could be considered as future market products.

V. CONCLUSION AND FUTURE WORKS

This paper presents an activation pattern for tertiary control reserves in order to improve frequency control performance. The activation of tertiary control reserves restores the deployed secondary control, and hence, increases the power system security.

Analyzing the Swiss power system control signal implies that the control signal at each time instant is composed of stochastic and deterministic components. An MPC technique is proposed to invoke tertiary control reserves in order to compensate for the deterministic portion of the control signal. The internal dynamic of MPC is a linear regression model, known as a location model, based on the data profile of the control signal. The MLE estimates the location of the control signal for an upcoming time period. An objective cost function is selected to satisfy the estimated control power by dispatching tertiary control reserves. This cost function considers the price, security criteria, and operating status of the reserves.

Different influence functions, corresponding to different distributions, are considered to estimate the control signal. All approaches have successfully decreased the saturations and daily peaks of the control signal. However, the Fair function, corresponding to the median of the control signal, demonstrates the best performance. Applying the pattern achieved also improves the deficit rate. The other interpretation of this result is that the Swiss TSO could keep the current deficit rate and decrease the power provision of positive secondary control reserves. Such a step would constitute a significant reduction of ancillary services costs.

In addition, analysis of the operating time illustrated that the TSO can request tertiary control reserves based on an operating time of 30 minutes which is more desirable compared to 15 minutes for suppliers. However, it costs slightly more than the scenario of 15 minutes operating time. Shorter operating tertiary control reserves can be considered as possible future products in the ancillary services market.

The proposed pattern is economically beneficial in light of the current activation prices in the Swiss ancillary services market; however, the market influence of the frequent activation of tertiary control reserves should be analyzed as a future work. Future research will address nonlinear regression models such as artificial neural networks.

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