

Hybrid Data-Model Predictive Control for Enabling Participation of Renewables in Regulating Reserves Service

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Abstract—A long-horizon hybrid data-model predictive direct power control (HD-MPDPC) scheme is proposed. The hybrid control scheme is for grid-side power electronic converters (PEC) in grid-connected renewable energy sources (RES). Computational burden of conventional MPDPC is alleviated by reducing the number of candidate voltage vectors to be examined in the cost function. This is achieved by employing data-driven forecast of RES output power to identify and eliminate the voltage vectors that do not counteract active and reactive power errors appropriately. RES power is forecasted using recurrent neural networks. The method for eliminating voltage vector candidates is inspired from direct power control, where output of active and reactive power hysteresis controllers along with the sector in which grid voltage vector lies are used to determine the switching states of the grid-side PEC. Thanks to reduced computational complexity, the hybrid predictive control scheme dispatches RES power more reliably over long horizons. This in turn enables RES as a regulating reserves service provider in power systems. Hardware-in-the-loop studies of a grid-connected wave energy conversion system verify reduced computational complexity of HD-MPDPC and its effectiveness in controlling RES output power over long horizons.

Index Terms—Power forecast, predictive control, regulating reserves, recurrent neural networks, renewable energy generation.

I. INTRODUCTION

As penetration of renewable energy in the power grid grows, power grid operators (PGO) are developing regulations requiring renewable energy sources (RES) to provide essential reliability services (ERS) for grid flexibility and stability. ERSs can be divided into operating reserves (OR), which are critical for maintaining the frequency of the grid within operational bounds, voltage support, power factor regulation, black start, etc. [1]. Fig. 1 shows a general classification of OR services, including subclasses and their respective temporal scales. For this work, the subclass regulating reserves (RegR) will be discussed in more details.

The RegR service deals with active power imbalances that exist between the scheduled generation and load under normal grid operation [2]. Unit commitment, through which a day

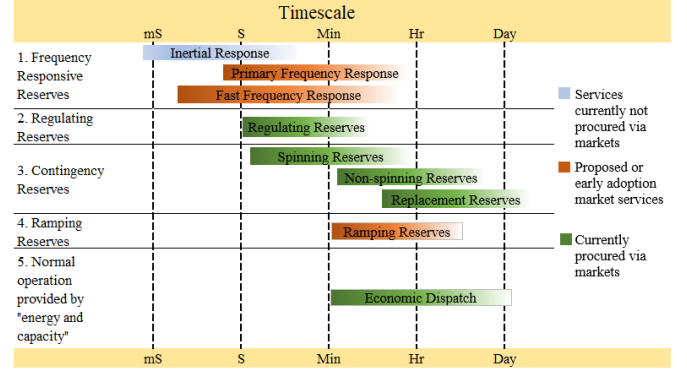


Fig. 1. General classification of operating reserve services [1].

ahead power system dispatch is planned, is solved by relying on the RegR service and balance of the active power mismatches caused by either varying load/generation or forecasting errors [1], [3]. Since RESs employ power electronic converters (PEC), their output power can be adjusted faster than traditional synchronous generators [4], [5]. Therefore, RESs can be considered as promising candidates for providing the RegR service. However, utilizing RESs for this purpose poses serious challenges due to intermittency and uncertainty of renewable energy.

In the literature, RES output power forecasting techniques employing physical, statistical, machine learning, fuzzy logic and hybrid methods have been extensively studied [6]–[11]. Despite good performance, some degree of prediction uncertainty is nevertheless present. Energy storage systems (ESS), if utilized, can resolve this problem by mitigating unpredicted power fluctuations [12].

In scenarios where utilizing an ESS is not a viable option, devising approaches with the ability to (i) predict future system behavior, (ii) accommodate constraints and nonlinearities, (iii) anticipate violation of bounds, and (iv) provide fast dynamic and good steady state performance becomes essential. Model predictive control (MPC), which offers these features, is proposed in applications where RES provides OR services [13], [14]. In [15], a controller that combines centralized-local Kalman filters with MPC is proposed to generate power reference signals for participation of individual wind turbine units in frequency regulation. In [16], a three-layer nonlinear MPC scheme is presented, where the upper-layer sends overall wind farm power command for frequency support to the middle-layer, power references are then distributed among the wind units and are sent to the bottom-layer for local control

execution. A control scheme for emergency frequency support among ac asynchronous areas connected through multi-terminal dc grid is studied in [17]. The model predictive controller produces power setpoints and provides a balance between dc voltage and ac frequency deviations.

In majority of the existing literature, including the above referenced ones, RESs employing MPC participate in fast and/or primary frequency response service. However, MPC's potential for enabling RESs participation in RegR service is not exploited. This is because longer prediction horizons (required for RegR service) in the grid-side PECs control scheme add to the computational complexity of MPC, making it almost infeasible to implement in real time.

Most recent strategies on reducing computational complexity of MPC for grid-connected PECs are discussed in [18]-[25]. Majority of those studies are focused on either multi-vector MPC [18], [19], [22], where multiple voltage vectors are applied in one control period to improve current and power quality, or multi-level converters [20], [23], [25] where the number of candidate voltage vectors is high due to multiple switching devices in the converter topology. Only few papers aim at extending the prediction horizon of single-vector model predictive algorithms for commonly used two-level PECs. In [21], computational load is alleviated by offline optimization. Drawback of such generalized predictive control algorithm is that all the operational, dynamic constraints may not be satisfied when the cost function is optimized offline. A receding horizon MPC strategy for a grid-connected voltage-source inverter with an LCL filter is proposed in [24]. Computational burden is reduced by employing a reduced model of the converter. However, the capacitor effect of LCL tank is neglected and only a single equivalent inductor is considered.

In this paper, a novel hybrid data-model predictive direct power control (HD-MPDPC) for grid-side PECs is presented. The main feature of the proposed method is long prediction horizon, which is achieved through a two-stage process. In the first stage, forecast of RES's output power (based on historical data) along with some measurements are used to generate a set of candidate voltage vectors, where in the second stage they are fed to a model predictive direct power controller to select the voltage vector that minimizes the power tracking error. Each stage has distinctive objectives. The main goal of the first stage is to exploit forecasted RES power and reduce the number of candidate voltage vectors to be examined by the model predictive direct power controller in the second stage. The purpose of the second stage is realization of multiple-step model predictive direct power control (MPDPC) for enabling more reliable dispatch of RES power, a necessity for regulating reserves in power systems.

Since HD-MPDPC is proposed for the grid-side dc-ac PEC in grid-connected RESs, it can be employed in PV systems with two-stage dc-dc-ac power conversion, and wind and wave energy conversion systems with back-to-back ac-dc-ac power conversion. Here, the real-time implementation feasibility of HD-MPDPC is verified by hardware-in-the-loop (HIL) studies of a grid-connected wave energy conversion system (WECS).

Comparatives studies between conventional MPDPC and proposed HD-MPDPC are carried out to show effectiveness of the proposed HD-MPDPC in enabling participation of WECS in RegR service. Digital implementation time of both methods are extracted. It is shown that for long prediction horizons, complexity of conventional MPDPC raises exponentially, whereas HD-MPDPC's implementation time rises linearly.

Major contributions of this paper are three fold

- Proposing a novel approach for reducing the number of candidate voltage vectors to be examined in multi-step MPDPC of grid-side PECs.
- Proposing a novel long-horizon data-model predictive control scheme with low complexity and real-time implementation feasibility.
- Illustrating effectiveness of the proposed HD-MPDPC in enabling participation of grid-connected RESs in RegR services through HIL and real-time simulations.

The paper is organized as follows: Section II overviews the WECS model, conventional MPDPC and RES power forecast method. Section III describes the proposed long-horizon HD-MPDPC. HIL results and discussions are presented in section IV. Conclusions are drawn in section V.

II. OVERVIEW OF WECS MODEL, MPDPC AND RES POWER FORECAST

A. WECS model

Direct-drive WECSs, which comprise a buoy and a linear generator, are considered in this paper. A simplified motion equation of the WECS, given in (1), along with the model of the linear permanent magnet generator (LPMG) in d - q coordinates, given in (2) and (3) are used to estimate the WECS output power, P_{WEC} [26].

$$F_{wave} = m_{tot}\ddot{x} + (\gamma_g + \beta_b)\dot{x} + K_g x \quad (1)$$

$$L_{ss} \frac{\omega}{|\omega|} p i_{ds} = -R_{ss} i_{ds} + X_{ss} i_{qs} - v_{ds} \quad (2)$$

$$L_{ss} \frac{\omega}{|\omega|} p i_{qs} = -R_{ss} i_{qs} - X_{ss} i_{ds} - v_{qs} + \omega \psi_{PM} \quad (3)$$

$$P_{WEC} = \frac{3}{2} \omega \psi_{PM} i_{qs} \quad (4)$$

Here, F_{wave} is the wave-induced force acting on the buoy, m_{tot} is the total mass of the buoy and translator of the LPMG, γ_d is the LPMG damping coefficient, β_d is the buoy damping coefficient, K_g is spring coefficient of the power take-off, x is the buoy position, and $\dot{x}$ is the buoy speed. P_{WEC} is the active power of the LPMG, L_{ss} and R_{ss} are the stator inductance and resistance of the LPMG, respectively, ψ_{PM} is the flux linkage of the permanent magnet, i_{ds} and i_{qs} are the LPMG stator current components in the d - and q -axis, respectively, v_{ds} and v_{qs} are the LPMG stator voltage components in the d - and q -axis, respectively, $X_{ss} = |\omega|L_{ss}$, $\omega = 2\pi\dot{x}/\lambda$, where λ corresponds to the pole width of the LPMG, and $p = d/dt$. Parameters of the WECS considered in this paper are provided in Table III.

B. MPDPC

MPC requires a model of the system to estimate future behavior of its states over a specific time horizon. In space

vector notation, the output current dynamics of the grid-side PEC with an L-filter is expressed as [27]

$$L_s p \mathbf{i}_{sgr} = \mathbf{v}_{conv} - \mathbf{v}_{sgr} - R_s \mathbf{i}_{sgr} \quad (5)$$

where, $\mathbf{v}_{sgr}$ and $\mathbf{i}_{sgr}$ are the grid voltage and converter output current space vectors respectively, R_s and L_s are the filter resistance and inductance, respectively, p is the derivative operator, and $\mathbf{v}_{conv}$ is the voltage generated by the converter, which is a function of the converter's switching states and the dc-link voltage.

Using the first-order forward Euler approximation to discretize (5) with sampling time T_s , the predicted converter current at time step $k + 1$ can be given by

$$\mathbf{i}_{sgr}(k + 1) = \left(1 - R_s \frac{T_s}{L_s}\right) \mathbf{i}_{sgr}(k) + \frac{T_s}{L_s} [\mathbf{v}_{conv}(k) - \mathbf{v}_{sgr}(k)] \quad (6)$$

The converter active and reactive powers are then predicted as

$$P_{gr}(k + 1) = \frac{3}{2} \Re\{\mathbf{v}_{sgr}(k + 1) \mathbf{i}_{sgr}^{conj}(k + 1)\} \quad (7)$$

$$Q_{gr}(k + 1) = \frac{3}{2} \Im\{\mathbf{v}_{sgr}(k + 1) \mathbf{i}_{sgr}^{conj}(k + 1)\} \quad (8)$$

where $\mathbf{i}_{sgr}^{conj}$ is the conjugate of $\mathbf{i}_{sgr}$. The future grid voltage, $\mathbf{v}_{sgr}(k + 1)$, can be estimated as

$$\mathbf{v}_{sgr}(k + 1) = \mathbf{v}_{sgr}(k) e^{j\omega_{gr} T_s} \quad (9)$$

where ω_{gr} is the angular frequency of $\mathbf{v}_{sgr}$.

The objective of MPDPC is to select the converter voltage vector that minimizes the error between the reference and predicted active and reactive powers, formulated as the following cost function

$$J = [P_{gr}^*(k + 1) - P_{gr}(k + 1)]^2 + [Q_{gr}^*(k + 1) - Q_{gr}(k + 1)]^2 \quad (10)$$

It is worth noting that a two-level grid-side PEC can produce eight voltage vectors; six active and two zero. Therefore, in conventional MPDPC, eight possible voltage vectors are examined in each sampling period and the voltage vector that minimizes (10) is selected and applied in the next period.

C. Forecasting RES power

Proper selection of the forecasting technique is directly associated to type of RES, as each resource, i.e., solar irradiance, wind and ocean waves, has its own characteristics. Several prediction techniques using past time-series data for short-term wave parameters forecasting, including cyclical models, extended Kalman filters, and regression models have been studied in the literature [28]. Recently, prediction methods employing Neural Networks (NN) have gained attention due to their ability to model nonlinearities and robustness to noise [29]. Recurrent neural networks (RNN) are a class of NNs with internal feedback connection and capable of capturing the dynamic temporal behavior of time-series data. A type of RNN called nonlinear autoregressive with exogenous inputs (NARX) has been applied for short-term prediction of wave surface elevation and WECS output power in [29] and [30], respectively. The results verify NARX suitability for these purposes and thus, it is considered for forecasting WECS power

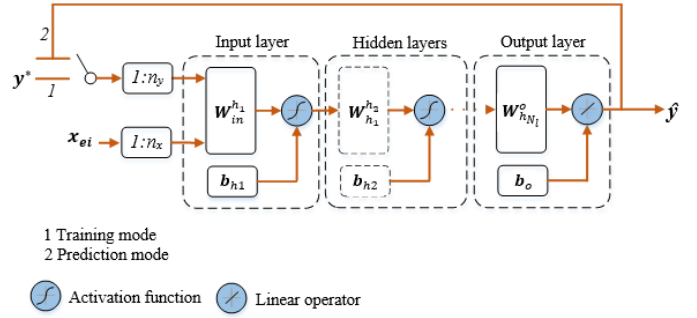


Fig. 2. NARX network architecture [30]

in this paper.

In NARX networks, the predicted output $\hat{\mathbf{y}} \in \mathbb{R}^{N_y}$ is obtained from the NARX model equation given by

$$\hat{\mathbf{y}}(k) = f(\hat{\mathbf{y}}(k - 1), \hat{\mathbf{y}}(k - 2), \dots, \hat{\mathbf{y}}(k - n_y), \mathbf{x}_{ei}(k - 1), \mathbf{x}_{ei}(k - 2), \dots, \mathbf{x}_{ei}(k - n_x), \Theta) \quad (11)$$

where f , $\mathbf{x}_{ei} \in \mathbb{R}^{N_x}$, n_x , n_y , and $\Theta = \{\theta_{in}, \theta_o, \dots, \theta_{h_{N_l}}\}$ are the mapping function, exogenous input, input time delay, output time delay, and trainable parameters of the network, respectively. $\theta_{in} = \{\mathbf{W}_{in}^{h1} \in \mathbb{R}^{n_x N_x + n_y N_y \times N_{h1}}, \mathbf{b}_{h1} \in \mathbb{R}^{N_{h1}}\}$, $\theta_o = \{\mathbf{W}_{o}^{hN_l} \in \mathbb{R}^{N_{h_{N_l}} \times N_y}, \mathbf{b}_o \in \mathbb{R}^{N_y}\}$, and $\theta_{h_{l-1}} = \{\mathbf{W}_{h_{l-1}}^{h_l} \in \mathbb{R}^{N_{h_{l-1}} \times N_{h_l}}, \mathbf{b}_{h_l} \in \mathbb{R}^{N_{h_l}}\}$ are sets of weight factors corresponding to the input layer, output layer, and the l^{th} hidden layer, respectively.

The architecture of a NARX network is depicted in Figure 2. In the training stage (position 1 of the switch), the network has a feedforward architecture, and both exogenous input $\mathbf{x}_{ei}$ and true output $\mathbf{y}^*$ are used to train the network parameters through static backpropagation. Once the training stage is completed (position 2 of the switch), true output $\mathbf{y}^*$ is removed and the predicted output $\hat{\mathbf{y}}$ is fed back to the input of the network.

III. HYBRID DATA-MODEL PREDICTIVE DIRECT POWER CONTROL

A scheme of HD-MPDPC is shown in Fig. 3. As described earlier, in the first stage, RES output power prediction combined with a novel methodology facilitate reducing the number of candidate voltage vectors. In the second stage, based on the desired power set by PGO, a multi-step model predictive direct power controller selects appropriate voltage vectors (from candidate voltage vectors) to be applied by the grid-side PEC. The following subsections provide details of the proposed hybrid control scheme.

A. WECS output power prediction

The proposed prediction model is shown in Fig. 4, where $P_{mech} = F_{LPMG} \dot{x}$, and $F_{LPMG} = \gamma_g \dot{x} + K_g x$ is the force acting on the LPMG. At each time step, actual values of wave height ζ_{WAVE} are fed into the position and speed prediction blocks along with their respective feedback vector signals of predicted values, i.e., $\hat{x}$ and $\hat{\dot{x}}$. Elements of these two vectors are later combined to generate the vector of predicted mechanical power,

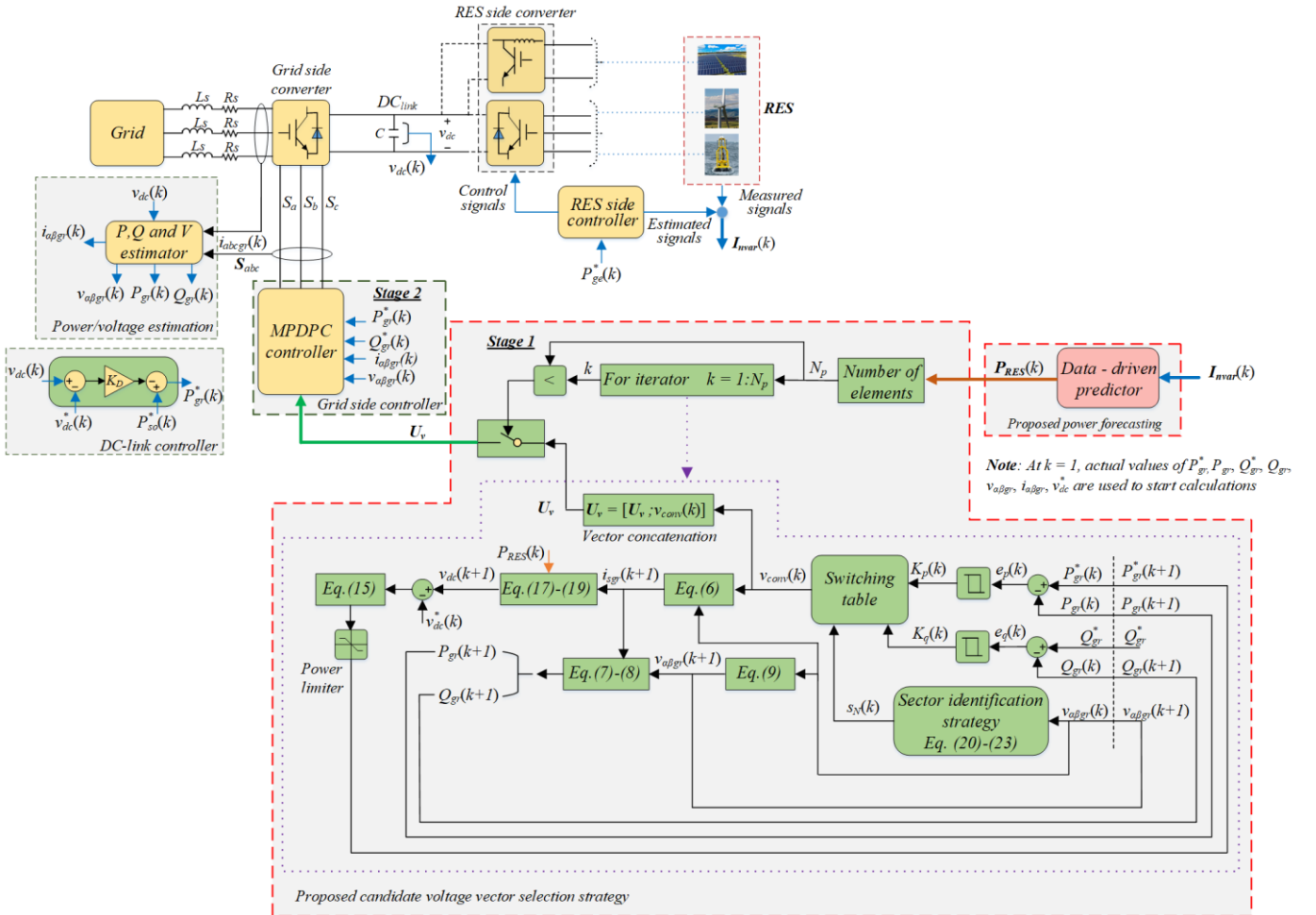


Fig. 3. Block diagram of the proposed HD-MPDPC

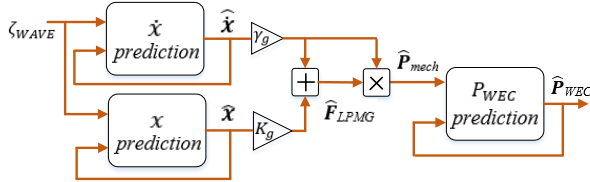


Fig. 4. Model for WECS output power prediction.

$\hat{P}_{mech}$. Finally, this vector is fed into the prediction block as the exogenous input along with the $\hat{P}_{WEC}$ feedback signal to yield new future estimates of generated wave power. Each neural network consists of 3 hidden layers with 5 neurons per layer, and 4 input delays and 4 output delays. The activation function between layers is the Sigmoid function.

A data set, containing buoy position and speed, and WECS output power profiles is generated. Parameters of the considered WECS are listed in Table III. The WECS output power profiles are produced using the model given by (1)-(4) for a period of 6000 s with a sampling frequency of 100 Hz. Wave time-series are obtained using the modified Pierson-Moskovitz wave spectrum with a SWH of 4 m, and dominant wave period (DPD) of 10.1 s. For training, 70% of the data points are employed, and the remaining 30% are employed for validation and testing. The forecasting accuracy is assessed using the mean squared error (MSE), normalized mean squared error (NMSE) and correlation coefficient (CC) indexes

 TABLE I
FORECASTING ACCURACY METRICS

NARX	Index	horizon [s]					
		1	2	5	10	25	
Position	MSE	5.23e-5	3.17e-4	0.0019	0.0057	0.0119	
	CC	0.9991	0.9953	0.9364	0.9113	0.7233	
Speed	MSE	2.54e-4	0.0011	0.0031	0.0062	0.0113	
	CC	0.9994	0.9931	0.9669	0.9143	0.6719	
Power	NMSE	0.0715	0.0902	0.1152	0.3125	0.7246	
	CC	0.9842	0.9613	0.9506	0.8972	0.6315	

expressed as

$$MSE = 1/N_y \|(\hat{y} - y^*)\|^2 \quad (12)$$

$$NMSE = \frac{\|(\hat{y} - y^*)\|^2}{\|(y^* - \mu_{y^*} \mathbf{1})\|^2} \quad (13)$$

$$CC = \frac{(y^* - \mu_{y^*} \mathbf{1})^T (\hat{y} - \mu_{\hat{y}} \mathbf{1})}{\|(y^* - \mu_{y^*} \mathbf{1})\| \|(\hat{y} - \mu_{\hat{y}} \mathbf{1})\|} \quad (14)$$

where $\mu_{\hat{y}}$ and μ_{y^*} are the mean of vectors $\hat{y}$ and y^* respectively, $\mathbf{1} \in \mathbb{R}^{N_y}$ is the vector of all ones, and $\|\cdot\|$ is the Euclidean norm.

Position and speed NARX networks are trained and tested individually for different prediction horizons. Levenberg–

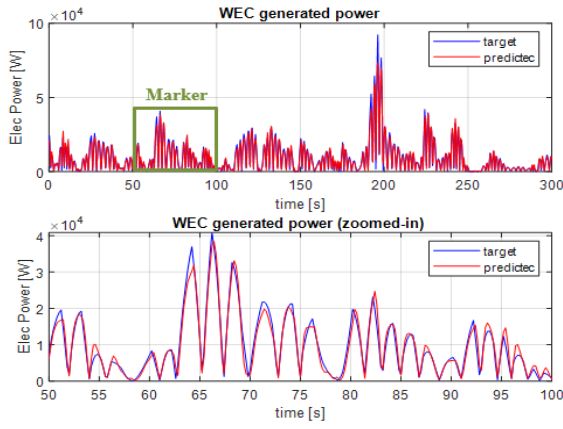


Fig. 5. Prediction results for WEC output power (top), marker zoomed-in section (bottom)

Marquardt algorithm is used to train the NN. Table I provides forecasting performance of both NARX networks. It is seen that the networks have good accuracy in the short-term, i.e., prediction horizons between 1 and 10 s, where the CCs are greater than 0.9 (highly correlated). It is worth noting that the future estimated values of position and speed, including their respective prediction errors, are mathematically combined to obtain WECS power (see Fig. 4). Therefore, performance of the power NARX network is slightly degraded when compared to the other two networks for the same prediction horizon.

As another comparison, real WECS power and forecasted power (with a prediction horizon of 5 s) are shown in Fig. 5. The WECS power time series is obtained by using a wave profile with SWH of 3.8 m and DPD of 8.7 s. The zoomed-in figure (marker) verifies that the proposed prediction model is capable of producing accurate future estimates of WECS power.

B. Reducing the number of candidate voltage vectors

As already mentioned, in conventional MPDPC with one step ahead prediction horizon, eight possible voltage vectors are examined in each sampling period. The number of candidate voltage vectors increases exponentially as the prediction horizon increases, imposing computational burden and complexity.

In this work, a methodology inspired from direct power control (DPC) is proposed for reducing the number of candidate voltage vectors. Table II provides a pseudo code for this methodology. At each sampling time, the algorithm receives forecasted RES power, P_{RES} , active power set by PGO, P_{so}^* , reference dc-link voltage, v_{dc}^* , actual converter output powers $P_{gr}(k)$ and $Q_{gr}(k)$, reference powers $P_{gr}^*(k)$ and $Q_{gr}^*(k)$, grid-side currents $i_{\alpha\beta gr}(k)$ and voltages $v_{\alpha\beta gr}(k)$ in $\alpha\beta$ coordinates, and dc-link voltage $v_{dc}(k)$ as inputs. The designated prediction horizon N_p and candidate voltage vector set $\mathbf{U}_v$ are defined. Active and reactive power errors, $e_p(k)$ and $e_q(k)$, are calculated and fed to corresponding hysteresis controllers. Also, the sector in which $\mathbf{v}_{sgr}(k)$ lies, i.e., $s_N(k)$, is identified. Next, sector information along with the output of hysteresis controllers K_p and K_q are used as inputs to a predefined switching table, where appropriate voltage vector to counteract power errors is selected. The selected voltage vector

TABLE II
PSEUDOCODE: CANDIDATE VOLTAGE VECTOR REDUCTION METHODOLOGY

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1. Inputs:  $P_{RES}$ , actual values of  $P_{so}^*(k)$ ,  $P_{gr}(k)$ ,  $Q_{gr}(k)$ ,  $P_{gr}^*(k)$ ,  $Q_{gr}^*(k)$ ,  $i_{\alpha\beta gr}(k)$ ,  $v_{\alpha\beta gr}(k)$ ,  $v_{dc}(k)$ ,  $v_{dc}^*$ 
2. Output:  $\mathbf{U}_v$ 
3. Parameters:  $\bar{e}_p$ ,  $\bar{e}_q$ ,  $K_p$ ,  $K_q$ ,  $K_D$ ,  $\underline{P}_{conv}$ ,  $T_s$ ,  $C_{dc}$ ,  $\omega_{gr}$ ,  $R_s$ ,  $L_s$ 
% define designated prediction horizon and candidate voltage vector set%
4.  $N_p = \text{size}(P_{RES})$ 
    $\mathbf{U}_v = \text{zeros}(N_p+1,1)$ 
% candidate voltage vector calculation%
At  $k=1$ , actual values of  $P_{gr}$ ,  $Q_{gr}$ ,  $P_{gr}^*$ ,  $Q_{gr}^*$ ,  $i_{\alpha\beta gr}$ ,  $v_{\alpha\beta gr}$ ,  $v_{dc}$ ,  $v_{dc}^*$  are used to start calculations. It is assumed  $Q_{gr}^*$ ,  $v_{dc}^*$  are kept constant.
5. for  $k=1$  to  $N_p$ 
% Power errors calculation %
6.  $e_p(k) = P_{gr}^*(k) - P_{gr}(k)$ 
7.  $e_q(k) = Q_{gr}^*(k) - Q_{gr}(k)$ 
% Sector Location strategy %
8. Eq. (20)-(23) produces  $s_N(k)$  using  $v_{\alpha\beta gr}(k)$ 
% Hysteresis controller for P and Q %
9. With  $e_p(k)$ ,  $e_q(k)$ ,  $\bar{e}_p$ ,  $\bar{e}_q$ , generate  $K_p(k)$ ,  $K_q(k)$ 
   if  $e_{p,q}(k) < -\bar{e}_{p,q}/2$ 
      $K_{p,q} = 0$ 
     go to line 10
   elseif
      $K_{p,q} = 1$  if  $e_{p,q}(k) > \bar{e}_{p,q}/2$ 
     go to line 10
   elseif
      $-\bar{e}_{p,q}/2 < e_{p,q}(k) < \bar{e}_{p,q}/2$ 
     apply same voltage vector of previous step
     go to line 11
   end
% Voltage vector selection %
10. With  $K_p(k)$ ,  $K_q(k)$ , and  $s_N(k)$  use switching table to generate  $\mathbf{v}_{conv}(k)$ 
% store selected voltage vector %
11.  $\mathbf{U}_v = [\mathbf{U}_v; \mathbf{v}_{conv}(k)]$ 
12. if  $k > N_p$ 
13. return  $\mathbf{U}_v$ 
14. else
% Update reference and estimated powers%
15. Eq. (9) updates  $v_{\alpha\beta gr}$ 
16. Eq. (6) updates  $i_{\alpha\beta gr}$ 
17. Eq. (7) and (8) update  $P_{gr}$ ,  $Q_{gr}$ 
18. Eq. (17)-(19) update  $v_{dc}$  %forecasted power  $P_{RES}$  is used in the calculation
19. Eq. (15) updates  $P_{gr}^*$ 
20.  $P_{gr}^*(k+1) = \min(-\underline{P}_{conv}, \max(\underline{P}_{conv}, P_{gr}^*(k+1)))$  %limit converter output
21. end
22. end

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is stored in $\mathbf{U}_v$ and later employed along with forecasted RES output power to calculate converter output current and dc-link voltage at time step $k+1$. In addition, future grid voltage is computed, and new predicted and reference grid powers are obtained. This process is repeated for all the time steps within N_p , i.e., $N_p + k$. Once the calculation process in this stage is completed, $\mathbf{U}_v$ is extracted and fed to the model predictive direct power controller in the second stage, where each element in $\mathbf{U}_v$ is examined to select the voltage vector that minimizes the power tracking error. It is noteworthy to mention that thanks to the proposed method, the number of candidate voltage vectors in $\mathbf{U}_v$ grows linearly with the number of prediction steps. This drastically reduces the computational complexity in stage two.

To calculate power errors at time step $k+1$, corresponding reference powers must be determined. As shown in Fig. 3, the reference active power P_{gr}^* is obtained from the dc-link controller, while reference reactive Q_{gr}^* is set by PGO. Here, dc-voltage droop control is adopted to regulate the dc-link

voltage by correcting power imbalances between generation and power delivered to the grid

$$P_{gr}^*(k+1) = P_{so}^*(k) - K_D(v_{dc}(k+1) - v_{dc}^*) \quad (15)$$

where K_D is the droop constant. In (15), predicted value of v_{dc} at time step $k+1$ is required for calculating $P_{gr}^*(k+1)$.

The dc-link capacitor dynamics can be determined by applying Kirchhoff's current law at the dc-link node

$$C_{dc} p v_{dc} = i_{ge} - i_{conv} \quad (16)$$

where C_{dc} is the capacitance of the dc-link capacitor, and i_{ge} and i_{conv} are the currents of RES and converter on the dc-link side, respectively. By discretizing (16), $v_{dc}(k+1)$ may be written as

$$v_{dc}(k+1) = v_{dc}(k) + \frac{T_s}{C_{dc}} [i_{ge}(k) - i_{conv}(k)] \quad (17)$$

where

$$i_{ge}(n) = P_{REG}(k)/v_{dc}(k) \quad (18)$$

$$i_{conv}(k) = i_{sa}(k)(S_1(k) - S_3(k)) + i_{sb}(k)(S_2(k) - S_3(k)) \quad (19)$$

In (19), $i_{sa}(k) = \Re\{i_{sgr}(k)\}$, $i_{sb}(k) = -1/2 \Re\{i_{sgr}(k)\} + \sqrt{3}/2 \Im\{i_{sgr}(k)\}$, and $S_i \in \{0, 1\}$ with $i \in \{1, 2, 3\}$ are the switching states of each converter leg.

As mentioned, in addition to power errors, the sector in which the grid voltage space vector lies must be determined. In DPC, S_N is determined by obtaining the angle of v_{sgr} , θ_s . This involves trigonometric functions, e.g., arctangent operator. Keeping in mind that digital processing of trigonometric functions imposes high computational burden, and the fact that S_N , and not θ_s is required for realizing the proposed method, a novel scheme employing only logic and arithmetic operators is proposed.

The method employs two auxiliary voltage vectors that are collinear with sectors boundaries and their projections on the α -axis are equal to α -component of v_{sgr} , $v_{\alpha gr}$. To visualize these voltage vectors, consider Fig. 6(a) for instance, where v_{sgr} lies in sector V. The auxiliary voltage vectors v'_{sgr} and v''_{sgr} share the same α -component with v_{sgr} and are collinear with boundaries between sectors IV-V and V-VI. The β -component of the auxiliary voltage vectors are $v'_{\beta gr} = \sqrt{3}/3 |v_{\alpha gr}|$ and $v''_{\beta gr} = \sqrt{3} |v_{\alpha gr}|$. It is clear that $v_{\alpha gr} < 0$, $v_{\beta gr} > 0$, $v_{\beta gr} - v'_{\beta gr} > 0$ and $v_{\beta gr} - v''_{\beta gr} < 0$. Sign of each of these inequalities is used to form vector $\mathbf{z} = [-1 \ 1 \ 1 \ -1]$. Following similar steps, sign combinations associated with every 12 sectors are obtained and $\mathbf{z}^T$ is stored as a column in matrix $\mathbf{D}$, given in (22). It should be mentioned that for sectors I, IV, VII and X two $\mathbf{z}$ vectors exist. Thus, matrix $\mathbf{D}$ is a 4×16 matrix. Finally, an indexing process is carried out to determine the column of $\mathbf{D}$ that shares the same elements of $\mathbf{z}^T$. The column number corresponds to the sector in which v_{sgr} lies.

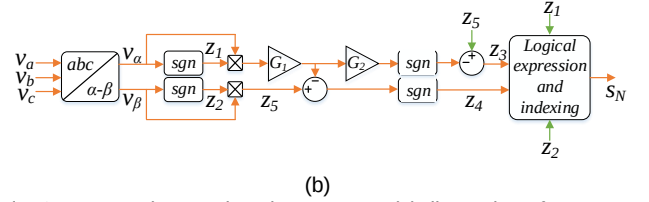
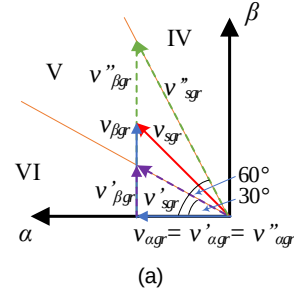


Fig. 6. Proposed sector location strategy. (a) Illustration of sector identification. (b) Block diagram.

Fig. 6(b) depicts the block diagram of the proposed sector selection method, where sgn is the sign function, and $G_1 = \sqrt{3}$ and $G_2 = 1/3$. Inside the logical expression and indexing block, the following rules are employed

$$\begin{aligned} \xi &= i \\ \text{such that} \\ \mathbf{d}_{*,i} &= \mathbf{z}^T \quad \text{for } i = 1, \dots, 16 \end{aligned} \quad (20)$$

and

$$S_N = r_{1,\xi} \quad (21)$$

Here, $\mathbf{d}_{*,i}$ is a vector that contains the i^{th} column of matrix $\mathbf{D}$, and $r_{1,\xi}$ is the ξ^{th} element of vector $\mathbf{r}$. It is noteworthy that $z_1, \dots, z_4$ in Fig. 6b form $\mathbf{z} = [z_1 \ z_2 \ z_3 \ z_4]$.

Matrix $\mathbf{D}$ and vector $\mathbf{r}$ are defined as follows

$$\mathbf{D} = \begin{bmatrix} 1 & 1 & 1 & -1 & -1 & -1 & -1 & -1 & -1 & 1 & 1 & 1 & 1 & 0 & -1 & 0 \\ 1 & 1 & 1 & 1 & 1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & 0 & 1 & 0 & -1 \\ -1 & 1 & 1 & 1 & 1 & -1 & -1 & 1 & 1 & 1 & 1 & -1 & -1 & 1 & -1 & 1 \\ -1 & -1 & 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 & -1 & -1 & -1 & 1 & -1 & 1 \end{bmatrix} \quad (22)$$

$$\mathbf{r} = [1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \ 10 \ 11 \ 12 \ 1 \ 4 \ 7 \ 10] \quad (23)$$

Following the proposed indexing process, for the example shown in Fig. 6(a), $\xi = 5$ and $S_N = r_{1,5} = 5$, which gives sector V as the location of v_{sgr} .

C. Multi-step MPDPC

RES output power prediction affects selection of the candidate voltage vectors stored in $\mathbf{U}_v$, thus some degree of uncertainty in terms of counteracting power deviations is inherently present. As a result, applying those voltage vectors directly by the grid-side PEC could undermine reliability of the RegR service that RES can provide. Model predictive control can anticipate and handle violation of bounds. Therefore, MPDPC is considered to address this issue.

As described earlier, the control objective of MPDPC is power tracking, formulated as the cost function in (10).

TABLE III
PARAMETERS OF HIL STUDIES

Grid	
Line Voltage (rms)	480 [V]
Frequency	60 [Hz]
Converter and filter	
Rated power	70 [KVA]
L_s	17.5 [mH]
R_s	0.12 [Ω]
DC-link voltage	1200 [V]
C_{dc}	50 [mF]
Droop constant	2 %
WECS [26]	
m_{tot}	0.6×10^6 [Kg]
K_g	0.56×10^6 [N/m]
γ_g	27×10^3 [Ns/m]
β_b	1.42×10^6 [Ns/m]
L_{ss}	31 [mH]
R_{ss}	0.29 [Ω]
Ψ_{PM}	23 [Wb]
λ	0.1 [m]

Evaluating (10) for each voltage vector $\mathbf{v}_{conv} \in \mathbf{U}_v$ results in a set of different values of the cost function. The vector that produces minimum power deviations, i.e., lowest value of J , is selected and applied in the next sampling time. With classical MPDPC and prediction horizon of N_p , 8^{N_p} number of voltage vector sequences must be evaluated within one sampling period. However, hybrid structure of the proposed method enables the model predictive controller to evaluate only N_p voltage vectors.

IV. HIL RESULTS AND DISCUSSIONS

HIL studies of the system shown in Fig. 3, where a back-to-back ac-dc-dc conversion stage interfaces a wave energy conversion system with the grid, are carried out to 1) compare the computational complexity of the proposed HD-MPDPC versus MPDPC proposed in [27], and 2) verify efficacy of multi-step HD-MPDPC in adjusting the RES output power when it operates as a RegR service provider.

The HIL setup consists of an OP4510 real-time simulator from Opal-RT Technologies Inc with a 4-core Intel Xeon® 3.2 GHz CPU and a TI TMS320F28335 DSP. The entire system, including the grid, WECS, interfacing PECs and generator-side PEC controller are modeled on the real-time simulator, and the grid-side PEC controller is implemented on the DSP. This is done so that an accurate digital implementation time of the grid-side PEC controller is obtained.

Table III lists parameters of the HIL studies. Sampling frequency of the real-time simulator is set to 20 kHz. A wave profile with SWH of 4.2 m and DPD of 10 s is used to obtain the WECS output power time-series. Trained NARX networks from section III are employed to forecast the WECS output power. The generator-side PEC controller follows the maximum power point tracking (MPPT) approach presented in [26]. However, when WECS operates as RegR service provider, generator derating is achieved by directly adjusting the d - and q -axis current setpoints of the generator-side PEC.

TABLE IV
COMPUTATIONAL TIME (HARDWARE-IN-THE-LOOP IMPLEMENTATION)

Method	Horizon N_p	Time (μ s)	Increment* %
MPDPC	1	3.6	
HDMPDPC	1	16.6	
MPDPC	2	20.4	466.7
HDMPDPC	2	37.5	125.9
MPDPC	3	118.5	3191.7
HDMPDPC	3	55.3	233.1
MPDPC	7	Not implementable	
HDMPDPC	7	122.6	638.5

*% increment = $100 \times [\text{compt time}(N_p) - \text{compt time}(N_p=1)] / \text{compt time}(N_p=1)$

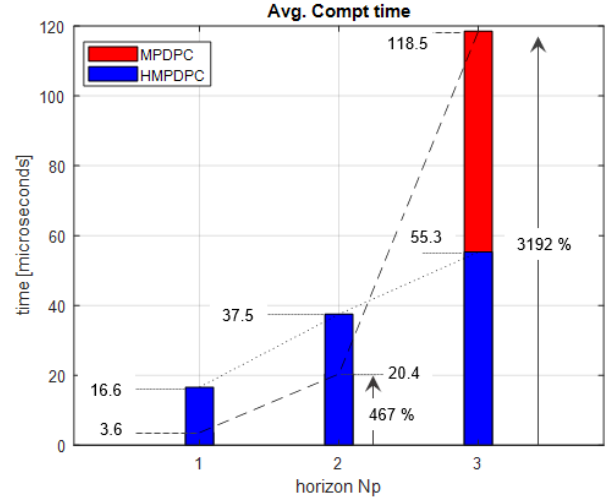


Fig. 7. Implementation time for one-, two- and three-step horizon

HIL studies are carried out when grid-side PEC is controlled under MPDPC and HD-MPDPC with $N_p = 1, 2$, and 3 . The computation time for each controller and time step is summarized in Table IV. For one prediction step, MPDPC shows marginally less computational burden than HD-MPDPC. For two prediction steps, however, MPDPC exhibits an increment of 466.7 % in computational effort when compared to 125.9% of HD-MPDPC. When the prediction horizon is further increased to three steps, the computational burden of MPDPC rises drastically, spiking to 3191.7% from 466.7%, showing 2725% increase. The computation time for three-step HD-MPDPC though, increases by only 107.2% (increasing from 125.9% to 233.1%). This demonstrates the exponential increase in computational time of MPDPC with longer prediction horizons and confirms efficacy of the hybrid data-model predictive control scheme in significantly alleviating the computational burden. Thanks to reduced computational complexity, it is possible to achieve a prediction horizon of $N_p = 7$ in HIL studies with HD-MPDPC, whereas conventional MPDPC is no longer implementable on the DSP. Fig. 7 illustrates the results of Table IV. Exponential versus linear increase in computational times of conventional MPDPC and HD-MPDPC is visible as the prediction horizon increases. With higher performance computational resources, the proposed HD-MPDPC could potentially pave the way for enabling participation of RESs in RegR services thanks to very long prediction horizons.

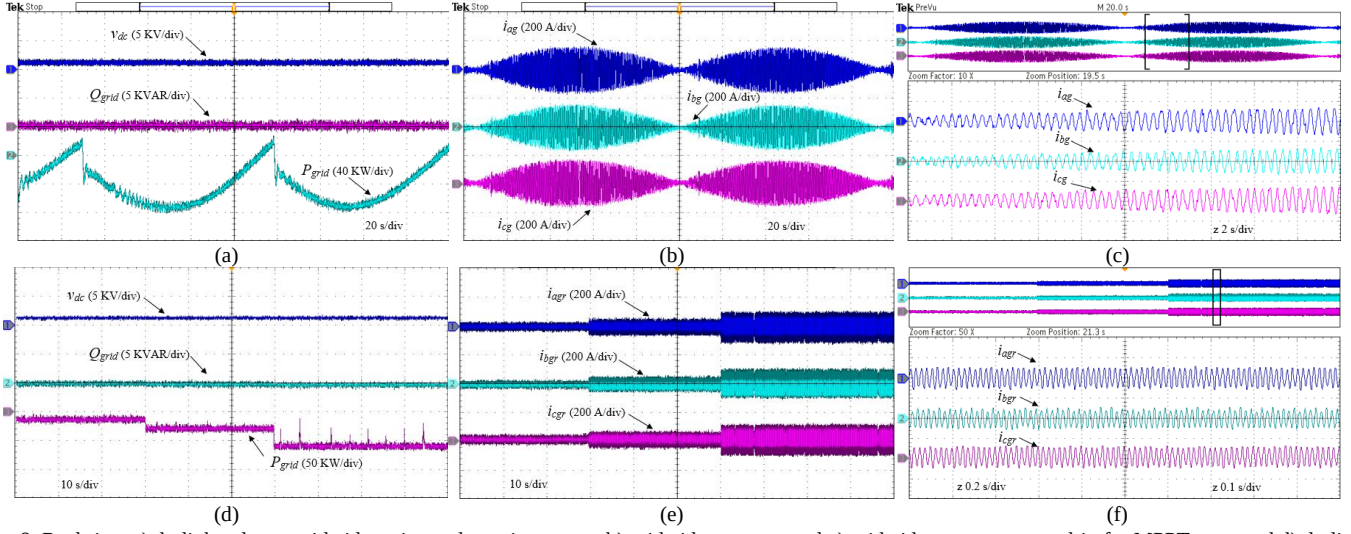


Fig. 8. Real-time a) dc-link voltage, grid-side active and reactive power, b) grid-side currents, and c) grid-side currents zoomed-in for MPPT case, and d) dc-link voltage, grid-side active and reactive power, e) grid-side currents, and f) grid-side currents zoomed-in for RegR service case (under HD-MPDPC).

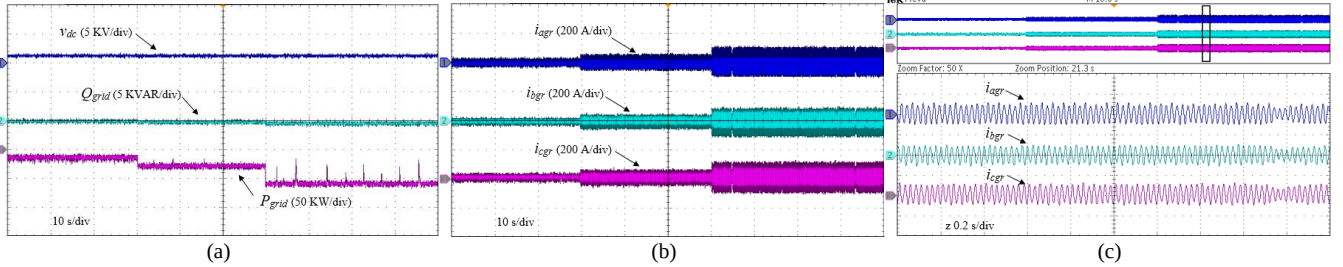


Fig. 9. Real-time a) dc-link voltage, grid-side active and reactive power, b) grid-side currents, and c) grid-side currents zoomed-in for RegR service case (under MPDPC in [31]).

To demonstrate how the proposed HD-MPDPC can regulate the output power of a RES in a long horizon, two scenarios are simulated in real time, where the entire system including grid-side PEC controllers are modeled on the OP4510 real-time simulator. In the first scenario, the generator-side PEC operates under MPPT mode and MPDPC with one prediction step is employed to control the grid-side PEC. Fig. 8(a) shows WECS generated power and dc-link voltage under MPPT mode. It is seen that MPDPC is able to adjust the reactive power and voltage at the dc link to their respective reference values. However, the injected active power to the grid exhibits large fluctuations associated to inherit variability of WECS generation. Thus, the PGO will not be able to rely on RES as RegR service provider.

In the second scenario, as shown in Figs. 8 (d)-(f), WECS generation capacity is pre-curtailed, and the proposed HD-MPDPC with 25 prediction steps is employed to control the grid-side PEC. Initially, under pre-curtailment regime, WECS is delivering 15 KW of active power, while the reactive power is kept at 0 KVAR. At $t = 30$ s, a power step of 25 KW is commanded by the PGO, increasing injected power to the grid from 15 KW to 40 KW, while maintaining $Q_{gr}^* = 0$. At $t = 60$ s, a further increase of 20 KW in active power is applied, adjusting the delivered active power to the grid to 60 KW. Despite the variable nature of WECS generation, the proposed multi-step HMPDPC is capable of tracking the reference values

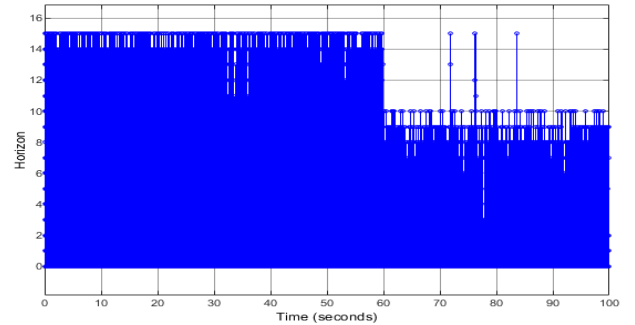


Fig. 10. Prediction horizon of MPDPC in [31].

of active and reactive powers, as well as keeping the dc-link voltage constant. Thanks to the long prediction horizon offered by HD-MPDPC, the PGO can rely on promised output power from RES, allowing its participation in RegR service.

Lastly, performance of HD-MPDPC is compared in real-time simulations with a multi-step MPDPC proposed in [31]. In [31], the switching horizon contains an ordered sequence of switch, denoted by “S”, and extend, denoted by “E”. When an “S” event occurs, the controller has the freedom to switch from the current input to a new input, advancing the prediction horizon by one time-step. When an “E” event occurs, the input is held constant, with the state and output trajectories extended until violation of the output constraints is predicted to occur, advancing the prediction horizon by a variable number of time-steps. This

gives rise to prediction horizons of varying length.

For a fair comparison between the two methods and to obtain similar power tracking error of HD-MPDPC in Fig. 8(d), MPDPC in [31] is implemented with eSE switching horizon, sampling frequency of 20 kHz (similar to HD-MPDPC), and active and reactive power bounds of 0.043 pu and 0.014 pu, respectively. Results are shown in Fig. 9. Slight reactive power tracking error is observed during the last step change in active power reference (from $t = 60$ s to $t = 100$ s). Also, varying length of prediction horizon is clear in Fig. 10, where the maximum achievable length is 15 steps, while HD-MPDPC is implementable with 25 prediction steps. Measured average switching frequency for MPDPC in [31] is 13.1 kHz, while for HD-MPDPC is 2.7 kHz. It is noteworthy to mention that the results reported in Table IV of [31] are obtained using a sampling frequency of 10 kHz and equal active and reactive power bounds of 0.060 pu, 0.08 pu, 0.100 pu and 0.120 pu. It is clear that lower sampling frequency and larger bounds lead to lower switching frequency, as also reported in [31]. However, for a fair comparison, those parameters are adjusted accordingly in this paper.

The comparative results confirm superiority of HD-MPDPC in terms of yielding longer prediction horizons, whilst offering slightly better power tracking performance and lower switching frequency.

V. CONCLUSION

The main innovation of this work lies in the hybrid data-model predictive framework, where by utilizing predicted RES output power and a novel candidate voltage reduction strategy, computational complexity of conventional multi-step MPDPC is reduced. Compared to conventional MPDPC, where 8^{N_p} number of voltage vector sequences are evaluated for a prediction horizon of N_p , hybrid structure of the proposed HD-MPDPC reduces that number to only N_p . HIL results verify the exponential versus linear increase of computational time for classical MPDPC and HD-MPDPC, respectively. Thanks to significant reduction in computational complexity, very long prediction horizons are achievable with HD-MPDPC. Assurance of reliable RES output power dispatch over long horizons allows PGOs to not only avoid excessive reserves in power system, but also consider RESs as a viable regulating reserves service provider.

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