An IDCNN based prediction horizon in extended state model of control technique of the converters

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Abstract: Model Predictive Control (MPC) could efficiently manage control problem with disturbances, complex constraints, and multi-control variables, and is extensively utilized in disparate control systems. As the cost function Prediction Horizon (PH) elevates, its complexity significantly augments. The existing approaches researched the optimum control sequence over a long PH, which is occasionally unnecessary and time-consuming. This paper proposed an IDCNN based PH in extended state model of control technique of the DC-DC converters to diminish the computation cost and ameliorate the performance. In this proposed methodology, the proposed Extended State Space (ESS) model of the DC to DC boost converters of Finite Control Set- MPC (FCS-MPC) is initially discussed. Next, the optimal PH is chosen by utilizing IDCNN. In Deep Convolutional Neural Network (DCNN), the Activation Function (AF) is done centered on radial basis function (RBF) and hence is termed as Improved DCNN (IDCNN). After examining the proposed system's performance, the proposed system is found to give a high-level performance.

Key words: *Extended state model of Finite control set-Model predictive control (FCS-MPC), Improved Deep Convolutional Neural Network (IDCNN), DC-DC boost converters and optimal prediction horizon.*

1. INTRODUCTION

Today, DC to DC converters [1] are extensively utilized in different industrial applications namely DC voltage supplies and are commonly utilized in DC smart grids, DC motor drives, new energy generation, battery charging/ discharging, hybrid vehicles, etc., [2]. It is also in power supplies as well as power drives for portable electronic devices [3]. A DC to DC converter, a switching circuit, transforms a certain electrical voltage to another level of voltage. This transformation is done by switches (open or closed) operating at higher frequencies; the control objective of these devices is to regulate the Output Voltage (OV) at the preferred value [4, 5]. On considering control, the prime challenge while governing this converter is to proffer a constant OV without regarding the variation in the current drawn from it by the load. The regulation of OV is not a minor task because this topology gives nonlinearities, non-minimum phase OV behaviour and also continuous- and discontinuous-conduction-modes under several operating scenarios [6]. The development of advanced control approaches along with the elevated computational power of the existing hardware in the control loop resolves the control problem in another new perspective [7]. Since DC-DC converters possess a complex hybridized nature, many techniques centered on hybrid modeling and control have been introduced recently [8]. Many improved control approaches, like sliding-mode control and fuzzy-neural control hysteresis control, have been examined in power electronic systems for controlling power converters. The practical applications of those controls are limited to a simple configured boost, buck, half- and full-bridge unidirectional converters topologies till today. Nonetheless, these controls are targeted to control more complex-configured converters topologies [9]. Only a few attempts were made where the modification of the reference is utilized to ameliorate the transient response of standard controllers [10].

The other remaining sections: Section 2 delineates the associated works. Section 3 detailed the proposed technique. Section 4 offers the experiential outcomes and as well section 5 deduces the paper.

2. RELATED WORK

L. Ortombina *et al* [11] suggested an FCS-MPC strategy for controlling the stator currents of a synchronous reluctance motor driven by a 3-level Neutral Point (NP) clamped inverter. The presented algorithm minimized the stator current distortions while operating the drive system at switching frequencies of a few hundred Hertz. To the end, a numerical calculation of the unconstrained solution of the optimization problem was introduced, along with modifications in the algorithm. Simulation outcomes evinced this control algorithm’s effectiveness.

Eyke Liegmann *et al* [12] proffered modifications to the sphere decoder encompassing the control of the NP potential of a 3-level NP clamped inverter. Here, the optimization problem of direct MPC was devised as an integer least-squares (ILS) one and tackled in a computationally effectual manner with a refined sphere de-coding algorithm. The usage of long PHs, that is, the system’s performance was notably ameliorated. This was elucidated with variable speed drives comprising a medium-voltage induction machine along with a 3-level NP clamped inverter.

Tobias Geyer *et al.* [13] derived an effectual optimization algorithm that tackled the control problem for extremely long PHs. It was attained by adapted sphere decoding principles. The algorithm needed only some computations and it directly proffered the optimum switch positions. As the computational load of the algorithm was effectually independent of the total of converter-output levels, this concept was specifically appropriate for multi-level topologies with countless voltage levels. The method was elucidated for the case of a variable speed drive system with a 3-level voltage source converter.

Sergio Vazquez *et al.* [14] rendered an MPC scheme for a Voltage Source Inverter utilized in a 3-phase UPS (i.e. Uninterruptible Power Supply) for critical loads. An MPC which was centered on continuous variables was utilized. The unconstrained MPC solution brought an explicit solution that was evaluated beforehand. Consequently, the effects of the PH length over the performance were also assessed. This control strategy was verified on a simulated design of a UPS that supplied a 3-phase resistor load. The simulation outcomes evinced that the continuous MPC controller attained high-level robustness and performance.

Ricardo P. Aguilera and Daniel E. Quevedo [15] propounded an adequate scenario for the local practical stability of a particular class of power converters controlled through FCS MPC which was designed as linear time-invariant systems with quantized input. Additionally, it also developed bounds on the steady-state behaviour of those systems. As an example, the approach applied the outcomes to a buck DC to DC converter, as well as to a two-level DC to AC inverter in a dq-coordinate frame.

3. PROPOSED METHODOLOGY

In the proposed IDCNN based PH in extended state model of FCS-MPC technique of the DC to DC boost converter, the ESS model of the FCS-MPC set is initially explained and the prediction process is then done by utilizing the IDCNN approach. The proposed method could be comprehended in detail using its block diagram evinced in Figure 1,

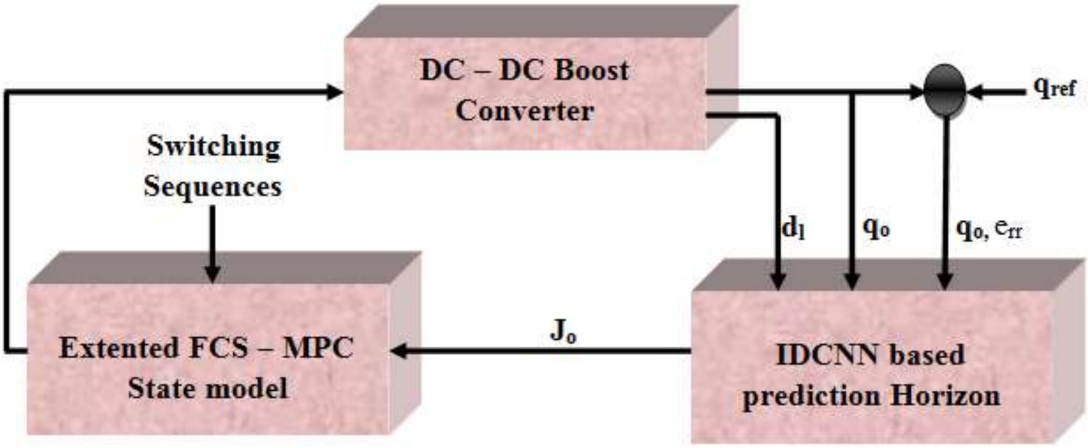


Figure 1: Block diagram for the proposed methodology

3.1 Extended state-space model of FCS-MPC

The DC to DC boost converter state-space model of the ESS model FCS-MPC is derived as shown in the below equations,

$$\Delta e_m(r+1) = X_m \Delta e_m(r) + Y_m \Delta z(r) \tag{1}$$

$$\Delta f_m(r+1) = Z_m \Delta e_m(r+1) \tag{2}$$

Where, $z(r)$, $e_m(r)$ and $f_m(r)$ indicates the input, state, and output of the model at time instant r, respectively, whereas, X_m, Y_m, Z_m signifies the system matrices with corresponding dimensions. In the equations (1) and (2), the state variable and the difference operator Δ are multiplied. Here, the reference trajectory $t(r)$ is evaluated as,

$$t(r) = f(r) \tag{3}$$

$$t(r+i) = \alpha^i f(r) + (1-\alpha^i) f_s \qquad i = 1,2,......., J \tag{4}$$

Here,

$f(r)$ - Actual process output,

f_s - Set-point,

α - Smoothing factor, and

J -PH.

Subsequently, the output tracking error at r could be elucidated as,

$$`c(r) = f_m(r) - t(r) \tag{5}$$

Where, $c(r)$ denotes the output tracking error at r. The formulation of $c(r+1)$ is done by combining the above equations (1)-(5).

$$c(r+1) = c(r) + Z_m X_m \Delta e_m(r) + Z_m Y_m \Delta z(r) - \Delta t(r+1) \tag{6}$$

Construct a new state variable as,

$$g(r) = \left[\Delta e_m(r)^T c(r)\right]^T \tag{7}$$

Then, the ESS model obtained by this proposed methodology is expressed as follows,

$$g(r+1) = Xg(r) + Y\Delta z(r) + z\Delta t(r+1) \tag{8}$$

The model's objective function (OF) is denoted as,

$$W_a = \sum_{\lambda=k}^{J} \left| q_{ref} - q_o(\lambda) \right| + \beta \left| m(\lambda - 1) - m(\lambda) \right| \tag{9}$$

Where, J indicates the PH over which the variables of interest are penalized, q_{ref} represents the reference voltage, and m signifies the switch position being either on or off and β specifies the weighting factor. The second term of the OF is utilized to avert excessive switching and lessen the switching frequency.

The FCS-MPC ascertains the optimal sequence amongst all viable switching sequences over the J. In enumeration, the OF cost, W_a is found for all those sequences and the sequence that returns the least cost is the optimal sequence. The first entry of this optimal sequence is the optimal switch position, which is then applied to the converter. This entire process is done within the sampling interval and is re-executed at every step as per the newest values of the states of the model.

The boost converter exhibits a non-minimum phase behaviour that entails an initial drop in the OV when the reference voltage is elevated. This behaviour needs a long PH which is sufficient to see the eventual rise of OV after it drops. A long PH also ameliorates the physical performance of the converter in the transient state where it aids to reach the reference voltage in a shorter time. Here, the load is also time-varying in many applications.

3.2 Prediction horizon method

The PH indicates the performance grounded on IDCNN. In this scheme, the PH is kept constant. A rise in PH ameliorates physical performance and also elevates the computational complexity. The purpose of this proposed method is to determine a PH that proffers a trade-off between physical performance and low computational complexity. This paper has a varying PH that adapts to the changing d_l, q_0 and $q_{0,err}$ values during disturbances in load, steady-states, changes in output reference voltage, and transients. The PH is centered on the cyber-physical cost function which is based on the sum of physical performance that means the total of the objective function W_a and the weighted cyber utilization W_b and is expressed as,

$$W_{ab} := W_a + \omega W_b \tag{10}$$

Where, ω indicates the weighting factor between the cyber cost and the physical cost. The W_b value elevates with J. Hence, a trade-off between physical performance and cyber utilization has to be found. The optimal PH, i.e., J_0 is the one that diminishes the cost W_b over J. In this proposed methodology, the optimal PH is found by utilizing the IDCNN which was expounded as follows,

The d_l, q_0, and the error between the output and reference voltages $q_{0,err}$ are provided as the input to the IDCNN classifier. The architecture of DCNN comprises pooling, fully connected, convolution, and also softmax layers. The DCNN classifier encompasses countless layers. The softmax layer fails to provide a good result, for this reason, the proposed methodology utilizes the RBF rather than the softmax layer. Short description of those layers is expounded as follows,

Convolution layer (CL): Here, each unit is linked to a local patch of units in the former layer via a collection of weights termed a filter. In this layer, the unit activation termed feature map is found by employing the non-linearity functions on the locally weighted sums.

Pooling layer (PL): The CL learns features, while, the PL integrates the semantically associated features into a single feature. Every unit in the PL takes input as of a patch of units of the former layer and gives a maximum or average of those values as output.

Fully-connected layer (FCL): In this layer, each unit is linked to the entire units in the former layer. Typically, the CL and PL are stacked in 2 or 3 stages before utilizing the FCLs.

RBF: It stands as a real-valued function and its value relies merely on the distance between the input and certain fixed points, either origin or other fixed points, namely a center. A function that fulfills the property is regarded as a radial function.

The IDCNN structure could be explicated in detail using Figure 2,

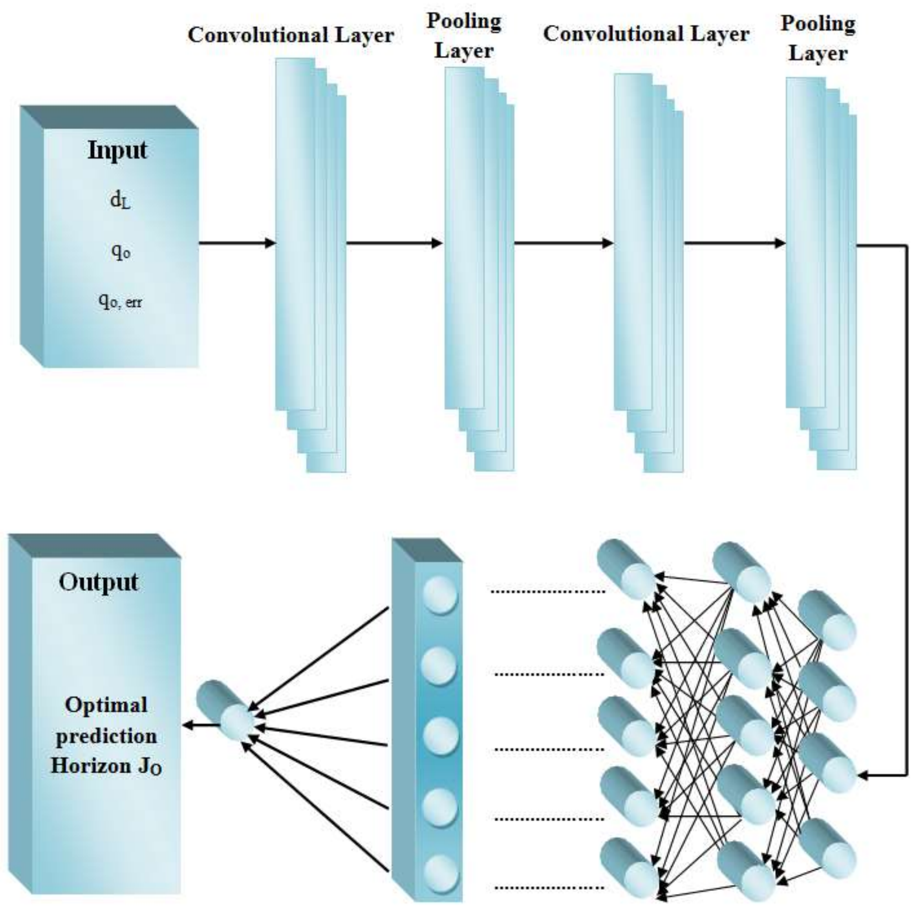


Figure 2: Structure of IDCNN

The AF proffers nonlinearities to the Convolutional Neural Network (CNN), which is necessary for the multi-layer networks for detecting nonlinear features. Consider $h_n(\cdot)$ as the nonlinear AF. The activation value h_n^s of convolutional feature h is evaluated as:

$$h_n^s = h_n(d_l, q_0, q_{0,err}) \tag{11}$$

The PL targets to attain shift-invariance by lessening the resolution of the feature maps. It is normally placed between '2' CLs. Each feature map of a PL is linked to its respective feature map of the preceding convolutional layer. By expressing the pooling function as $o(\cdot)$ for every feature map h_n , it have:

$$p_l = o\left(\left(h_n^s\right)\right) \tag{12}$$

Here,

p_l - pooling layer

The typical pooling operations are average pooling and max pooling.

After several CL and PL, there may be one or more FCLs that target to execute high-level reasoning. The FCL function is indicated as f_c. They consider all neurons in the former layer and link them to each neuron of the current layer for generating the global semantic information.

Lastly, the AF of the proposed DCNN is expressed grounded on the RBF. An RBF returns a value that relies only on the distance between ‘2’ points, one of which is a centre. And, it also returns a value grounded on the Euclidean distance from a point f_c to an RBF centre c_r. The computation of RBF I_f is given in equation (13):

$$I_f\left(f_c, c_r\right) = \exp\left(\frac{\left\| f_c - c_r \right\|^2}{2\delta^2}\right) \tag{13}$$

Where, δ represents standard-deviation controlling the width of a Gaussian curve. The gaussian curve indicates the region around the RBF centre which is of great importance. The AF for this DCNN is expressed as,

$$J_0 = \sum_i^N \psi_i \, v_i \left(I_f\left(f_c, c_r\right)\right) + b \tag{14}$$

Here,

J_0 - Output function that means the optimal PH

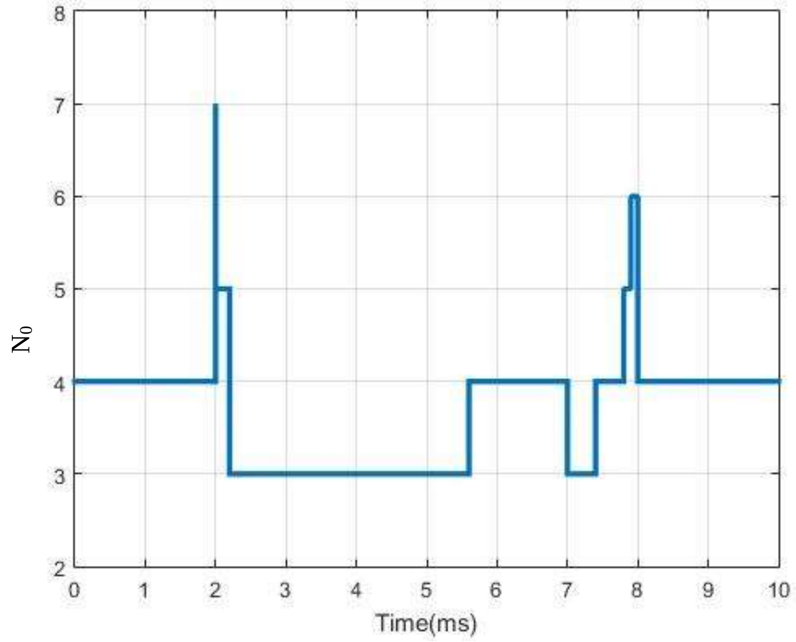
v_i - Hidden layer output,

ψ_i - Weight value and

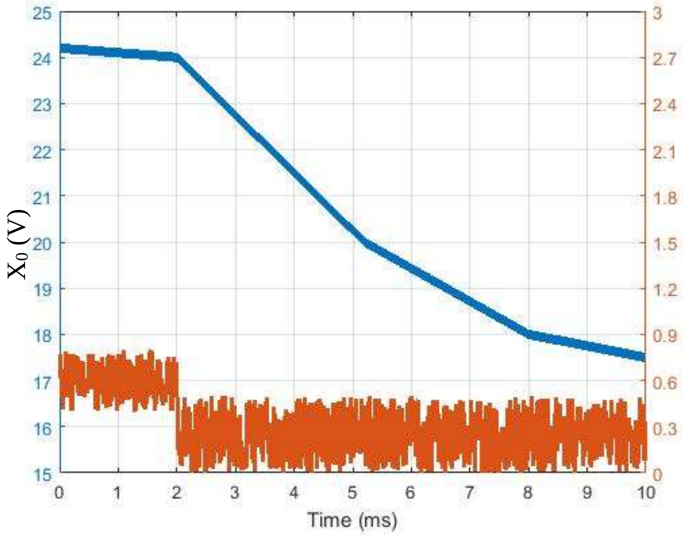
b - Bias function.

4. RESULT AND DISCUSSION

Here, the proposed system's performance is analyzed. Implement the proposed IDCNN based extended state model of FCS-MPC in the working platform of MATLAB/Simulink. Figs 3 and 4 proffer the down and up reference output voltage analyses.



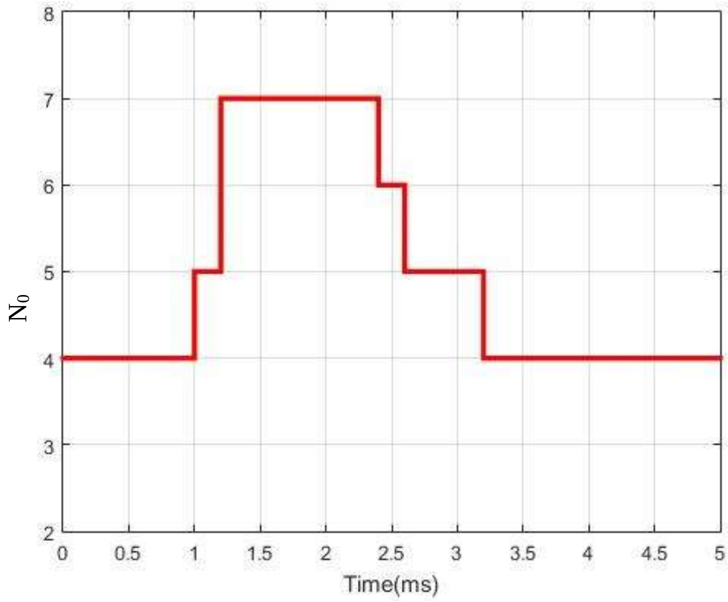
(a)



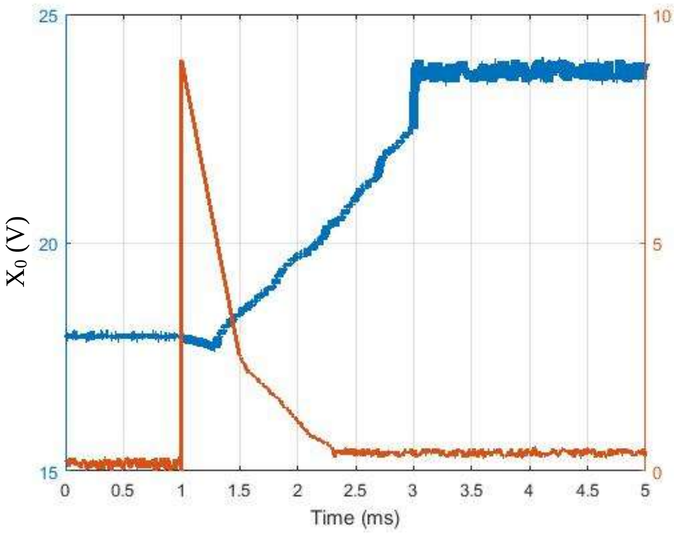
(b)

Figure 3: down reference output voltage of the proposed system

Figure 3 (a) and (b) evinces the optimal PH of the proposed methodology and the reference output voltage. The performance is gauged in the time interval of milliseconds. The time varies from 0 to 10ms.



(a)



(b)

Figure 4: up reference output voltage of the proposed system

Figure 4 shows the proposed PH system during step-up reference voltage. Figure 4 (a) is the optimal PH result during step-up voltage and Figure 4(b) shows the OV.

5. CONCLUSION

Recently, the integration of MPC and machine learning frameworks has achieved increasing attention. In industries, the MPC has a noteworthy role. In MPC, the performance is improved based on PH. If the PH performance is elevated, then the computational cost becomes high. In order to avoid the computational cost problem and to elevate the performance PH, this paper proposed an IDCNN based PH in an extended state model of control technique of the DC-DC converters. In this proposed model, the ESS model of the FCS-MPC is regarded. The optimal PH is done by utilizing the IDCNN approach. During performance analysis, the performance shown by the proposed system is analyzed centered on up reference output voltage and down reference output voltage. The outcomes corroborated that the proposed system shows high-level performance.

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